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Performance of Quantitative Investment Funds

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in the field of Economics and Finance

Dissertation written under the supervision of

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Podziękowania

Pragnę złożyć serdeczne podziękowania mojej promotor Pani dr hab., prof. ucz. Renacie Karkowskiej, bez której ta praca by nie powstała. Dziękuję za wieloletnią opiekę naukową, nieocenioną pomoc, życzliwość i zaufanie.

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Abstract

The objective of this thesis is to evaluate the performance of quantitative funds in relation to the performance of qualitative funds. This thesis aims to answer the question of whether state-of-the-art and automated approaches to portfolio management guarantee higher performance compared to traditional approaches. By applying a variety of performance measures and econometric models, this study focuses on a sample of nearly three hundred thousand investment funds in the period from 01/01/2000 to 31/12/2020. The examined funds apply various strategies and invest in many different regions. The study conducted allowed to state that the differences in performance between quantitative and qualitative funds vary between strategies and the geographic regions of a primary investment focus. Quantitative funds do not guarantee the outperformance of traditionally managed funds. The conclusions coming from this study may be valuable to managers considering the implementation of quantitative approaches to portfolio management and investors wondering if the application of state-of-the-art approaches to portfolio management results in higher performance.

Key words

Investment funds, performance, weak-form informational efficiency, quantitative funds, portfolio management

Efektywność funduszy inwestycyjnych typu ilościowego

Abstrakt

Celem pracy jest ocena efektywności inwestycyjnej funduszy typu ilościowego w porównaniu z funduszami zarządzanymi tradycyjnie. Praca stara się odpowiedzieć na pytanie, czy nowoczesne i zautomatyzowane podejścia do zarządzania portfelem gwarantują wyższą efektywność w porównaniu z metodami tradycyjnymi. Wykorzystując liczne miary efektywności oraz modele ekonometryczne, badanie skupia się na próbie blisko trzystu tysięcy funduszy inwestycyjnych, w okresie od 01/01/2000 do 31/12/2020. Badane fundusze wykorzystują różne strategie oraz inwestują w wielu różnych regionach. Przeprowadzone badanie pozwala twierdzić, że różnice w efektywności pomiędzy funduszami ilościowymi i funduszami zarządzanymi tradycyjnie, kształtują się w różny sposób dla poszczególnych strategii i głównych geograficznych regionów inwestycji. Fundusze ilościowe nie gwarantują wyższej efektywności w porównaniu z funduszami zarządzanymi tradycyjnie. Wnioski płynące z tego badania mogą stanowić szczególną wartość dla menadżerów rozważających wdrożenie nowoczesnych i zautomatyzowanych metod zarządzania portfelem oraz dla inwestorów zastanawiających się, czy wykorzystanie wspomnianych metod zaowocuje wyższą efektywnością.

Słowa kluczowe

Fundusze inwestycyjne, efektywność, efektywność informacyjna w formie słabej, fundusze ilościowe, zarządzanie portfelem

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Introduction

The motivation and the essence of the study

Inevitable and systematic technological progress in the area of Information Technology and Computer Science also has an impact on the way how investment funds manage their assets and make investment decisions. Some asset managers decided to utilize the results of technological progress in order to develop and implement automated, rules-based and objectified portfolio management processes. Investment funds in which investment decisions are based on the indications of a predefined automated investment process with none or a limited human intervention are mostly called *quantitative funds* or *quant funds* (e.g., Chincarini & Kim, 2006; Chincarini, 2014; Abis, 2018; Parvez & Sudhir, 2005; Guida, 2019; Fabozzi & Markowitz, 2011), as well as *systematic funds* (e.g., Harvey et al., 2017; Chuang & Kuan, 2018). Also, there seems to be the lack of complete consensus when it comes to nomenclature pertaining to investment funds, which do not rely on such predefined automated investment processes. In the issue-related literature and financial media they are mostly called *qualitative funds* (e.g., Chincarini & Kim, 2006; Chincarini, 2014), *discretionary funds* (e.g., Abis, 2018; Chuang & Kuan, 2018) or *fundamental funds* (e.g., Parvez & Sudhir, 2005; Guida, 2019; Fabozzi & Markowitz, 2011). Researchers raising the issue of investment funds that rely on a predefined automated investment process tend to propose their own definitions of such funds and their contrary parts, namely investment funds in which the investment process is not automated and investment decisions are made by human managers. The definitions proposed in the issue-related studies do not seem to be fully consistent, as they indicate various criteria that have to be fulfilled in order to qualify a fund into one of two groups. Nevertheless, proposed definitions appear to share many common elements, which makes them similar in terms of the substance of the problem. The heavy reliance on a predefined automated investment process, the utilization of advanced mathematical models, and the limited interventions of human managers in the portfolio management process can be examples of features commonly assigned to quantitative portfolio management, namely, the approach to portfolio management applied by quantitative funds. On the other hand, a heavy reliance on the judgement, skills, and intuition of a human manager, as well as the lack of the usage of a predefined automated investment process, are mostly proposed features of qualitative portfolio management, namely, the approach to portfolio management applied by qualitative funds. Taking into account no general consensus in terms of nomenclature, in further considerations, terms *quantitative funds* and *qualitative funds* will be used.

Researchers indicate that quantitative and qualitative approaches to portfolio management are often combined. Such approaches are mostly called *quantamental* (e.g., López de Prado, 2018; Arslanian & Fisher, 2019; Gray, Vogel, & Foulke, 2015; Svetlova, 2018) or *hybrid* (e.g., Fabozzi et al. , 2008). The combination of quantitative and qualitative approaches may take various forms (e.g., Guida, 2019; Fabozzi et al., 2008; Narang, 2013).

Despite the existence of investment funds that combine quantitative and qualitative approaches to portfolio management, researchers studying the performance of quantitative funds, in the majority of cases, conduct a comparative study between the two groups of funds, i.e., quantitative and qualitative funds. A group of funds that combines the features of quantitative and qualitative funds is not distinguished and considered as one of the groups that are compared. The reason for this is that the information included in financial databases does not allow to determine the level of being quantitative or qualitative. Moreover, most financial databases do not provide any information on whether a fund is quantitative or qualitative. Thus, in the majority of issue-related studies, researchers had to come up with their own ideas on how to split a universe of investment funds into quantitative and qualitative groups. Studies raising the issue of the performance of quantitative funds assume that the group of quantitative funds applies more quantitative techniques of portfolio management and aim to learn about the relative importance of their application in terms of generated performance (Chincarini, 2014).

Similarly to the previous issue-related studies, the study conducted for the needs of this thesis considers performance as the outcomes of activities taken in a specific time period. The performance evaluation process taken in the studies dedicated to the evaluation of the performance of quantitative funds provides information regarding historical results and investment-related costs. The foregoing issue-related studies focused on various universes of investment funds obtained from different financial databases and applied various research methodologies. Most studies considering the performance of quantitative funds suggest that quantitative funds mostly outperformed qualitative funds (e.g., Chincarini, 2014; Harvey et al., 2017; Parvez & Sudhir, 2005; Chuang & Kuan, 2018).

The aforementioned issue-related studies usually focused on particular investment fund types, such as hedge funds or equity funds. Their research samples rather did not exceed eleven thousand investment funds. The study conducted for the needs of this thesis utilizes a much larger sample consisting of nearly three hundred thousand live and dead funds coming from the Thomson Reuters Eikon database. According to the knowledge of the author of this thesis, this database was not applied in the issue-related studies. Hence, it would be interesting to see if the results of the study conducted with data retrieved from a different database allow to draw conclusions similar to those drawn on the basis of the results obtained in the previous studies. What is more, this study is dedicated to investment funds coming from four different groups of funds distinguished in terms of the applied strategy according to the Lipper Global Classification, i.e., equity funds, mixed asset funds, absolute return funds, and hedge funds. Such groups of funds like mixed asset funds and absolute return funds were not the objects of the previous issue-related studies. Furthermore, this study evaluates the performance of quantitative funds at the level of four most numerous groups of funds distinguished in terms of the region of a primary investment focus. The analysis of the results at the level of individual groups of funds distinguished in terms of strategy and region may reveal some interesting observations pertaining to differences in the performance of quantitative funds. Moreover, the study conducted for the needs of this thesis also focuses on the features of the returns of quantitative funds in terms of the weak-form informational efficiency. This part of the study refers to the advantage of quantitative funds over qualitative funds, which is commonly proposed in the issue-related literature, pertaining to the elimination of behavioural errors (Chincarini, 2014; Chincarini & Kim, 2006; Parvez & Sudhir, 2005). Such characteristics were not studied in the foregoing publications dedicated to the evaluation of the performance of quantitative funds. Additionally, this study evaluates the performance of quantitative funds in periods of low weak-form informational efficiency of equity markets. This part of the study refers to the beliefs of some researchers (Chincarini, 2014; Parvez & Sudhir, 2005) that quantitative funds take advantage of informational inefficiencies of financial markets in a better way compared to qualitative funds. All the abovementioned features of the study conducted for the needs of this thesis aim to fill the research gap in the area of the evaluation of the performance of quantitative funds.

Research objectives and hypotheses

The main research objective of this thesis is the evaluation of the performance of quantitative funds in relation to the performance of qualitative funds. The evaluation of the performance of quantitative funds in relation to the performance of qualitative funds will allow to learn about the relative importance of the application of quantitative portfolio management in terms of generated performance. The main research objective is directly related to the H1 hypothesis:

H1: The performance of quantitative funds is higher than the performance of qualitative funds.

The main research hypothesis has its grounds in the studies by Harvey et al. (2017), Chincarini (2014), Parvez and Sudhir (2005), and Chuang and Kuan (2018), which constituted a major part of the studies on the performance of quantitative funds. They suggest that in most cases, quantitative funds performed better compared to qualitative funds. A sample of the study conducted for the needs of this thesis also consists of other fund types, such as absolute return and mixed asset funds, which were not examined in the issue-related studies. However, it seems that the application of quantitative portfolio management techniques in such fund types may be beneficial. Absolute return funds aim to generate positive returns with low volatility, which are independent of the conditions on financial markets and conventional benchmarks. Mixed asset funds combine different asset types to create a portfolio. The commonly proposed advantages of quantitative funds over qualitative funds in areas such as the breadth of selection and risk management should enhance the performance of quantitative funds in such types of funds (Chincarini, 2014).

This thesis also aims to answer some supplementary research questions that may detail knowledge about the performance of quantitative funds. The first supplementary research question pertains to the similarity of quantitative funds to qualitative funds in terms of the homogeneity of performance generated. The second supplementary research question pertains to the similarity of quantitative funds to qualitative funds in terms of the correlation between their raw returns. These two questions refer to the study by Harvey et al. (2017) in which the results suggested that systematic and discretionary funds (as they called them) were quite similar in terms of performance dispersion and performance correlation. Such conclusions were not in line with common beliefs that systematic funds were highly homogenous and highly correlated due to the similarities of their strategies (Harvey et al., 2017). By providing the answers to the first and second supplementary questions, this study aims to verify whether it is possible to obtain results similar to those obtained by Harvey et al. (2017).

The third supplementary research question relates to differences in performance between quantitative and qualitative funds that may possibly differ between the groups of funds distinguished in terms of strategy and the region of a primary investment focus. By making an attempt to answer this question, this study may indicate the groups of investment funds in which the application of quantitative portfolio management may be especially beneficial.

The fourth supplementary research question refers to a possible connection between the fund size and its performance. According to Chincarini and Kim (2006), the development of a quantitative investment process may require to devote high capital expenditures; however, once a quantitative investment process is in place, the cost of portfolio management may become lower compared to qualitative portfolio management. The quality and performance of a quantitative investment process may be related to initial capital expenditures incurred for its development. Larger investment funds may be able to invest more in the development of quantitative investment processes that are more advanced and allow to generate higher performance. Thus, it is worth verifying whether larger quantitative funds perform better than smaller quantitative funds.

The fifth supplementary research question refers to the risk related to the distribution of returns generated by quantitative funds. The sixth supplementary research question pertains to the systematic risk of quantitative funds. According to Chincarini and Kim (2006), quantitative portfolio management is better than qualitative portfolio management in measuring and controlling the risk. The results of the study by Harvey et al. (2017) indicated that systematic funds (as they called them) were less exposed to risk factors compared to discretionary funds. Abis (2018) proposed that quantitative funds have better risk management and portfolio diversification throughout the business cycle. It will be interesting to verify whether, also in the case of the study conducted for the needs of this thesis, quantitative funds appear to be less risky.

The seventh supplementary research question relates to the possible higher performance of quantitative funds compared to their relevant equity market benchmark selected in this study. This study aims to evaluate the performance of quantitative funds in relation to the performance of qualitative funds. However, the evaluation of the performance of quantitative funds in relation to their relevant equity market benchmarks may constitute an additional insight on the issue of the performance of quantitative funds. All supplementary research questions related to the main research objective are as follows:

1. Are quantitative funds similar to qualitative funds in terms of the homogeneity of performance generated?
2. Are quantitative funds similar to qualitative funds in terms of the correlation between their raw returns?
3. Do the differences in performance between quantitative and qualitative funds differ between the groups of funds distinguished in terms of strategy and the region of a primary investment focus?
4. Do larger quantitative funds perform better than smaller quantitative funds?
5. Are quantitative funds less risky than qualitative funds in terms of risk related to the distribution of returns they generate?
6. Are quantitative funds less exposed to systematic risk than qualitative funds?
7. Do quantitative funds outperform their relevant equity market benchmark selected in this study?

Furthermore, two supplementary research objectives have been formulated in order to extend and detail the study. The first supplementary research objective is the evaluation of the weak-form informational efficiency of quantitative funds in relation to qualitative funds. The first supplementary research objective is directly related to the H2 hypothesis:

H2: The weak-form informational efficiency of quantitative funds is higher compared to qualitative funds.

The issue-related literature suggests that investment decisions of a qualitative portfolio manager can be affected by some behavioural biases. In the case of quantitative portfolio management, the model determines investment decisions, thus, the impact of a human factor is minimised (Chincarini & Kim, 2006; Chincarini, 2014). Behavioural errors, which occur in the case of qualitative portfolio management, may negatively affect the weak-form efficiency of qualitative funds. Thus, due to the possibly lower vulnerability of quantitative portfolio management to behavioural errors, quantitative funds may be marked by a higher weak-form efficiency. In the context of investing in quantitative funds, their higher weak-form efficiency may suggest a lower possibility of generating abnormal returns by investors and a lower predictability based on historical returns (Zamojska, 2012).

In addition, some further supplementary research questions have been posed with regard to the H2 hypothesis. By answering the next supplementary research question, this study will provide information on the lowest levels of the weak-form informational efficiency of equity markets. Furthermore, the study will provide information on the difference between quantitative and qualitative funds in terms of their weak-form efficiency in periods of low weak-form efficiency of equity markets. The minimisation of behavioural errors by quantitative funds proposed by Chincarini and Kim (2006) and Chincarini (2014) should be especially beneficial in periods of the exceptional instability of financial markets. The supplementary research questions pertaining to the first supplementary research objective are as follows:

8. Which periods were marked by the lowest levels of the weak-form informational efficiency of equity markets?
9. Are quantitative funds more weak-form efficient than qualitative funds in periods of low weak-form efficiency of equity markets?

Furthermore, with regard to the first supplementary research objective, this study aims to find out whether the differences in the weak-form informational efficiency between quantitative and qualitative funds differ between the groups of funds distinguished in terms of strategy and the region of a primary investment focus. Moreover, referring to the aforementioned possibility of developing and implementing more advanced quantitative investment processes by larger quantitative funds, this study aims to verify whether larger quantitative funds are more weak-form efficient compared to smaller quantitative funds. Such a difference may result from a possible advantage of larger quantitative funds in terms of possessing more advanced quantitative investment processes, which are also less vulnerable to behavioural errors. Additionally, the answer to the question of whether quantitative funds are more weak-form informationally efficient than their relevant equity market benchmark selected in this study will constitute additional insight on the weak-form efficiency of quantitative funds.

The second supplementary research objective is the evaluation of the performance of quantitative funds in relation to the performance of qualitative funds in periods of low weak-form informational efficiency of equity markets. The second supplementary research objective is directly related to the H3 hypothesis:

H3: Quantitative funds perform better than qualitative funds in periods of low weak-form informational efficiency of equity markets.

The second supplementary research hypothesis H3 has its grounds in the beliefs of some researchers (Chincarini, 2014; Parvez & Sudhir, 2005) that quantitative funds take advantage of informational inefficiencies of financial markets in a better way compared to qualitative funds. This study verifies these beliefs by evaluating the performance of quantitative funds in relation to the performance of qualitative funds in periods of the lowest efficiency of equity markets. Information on periods of the lowest efficiency of equity markets will be obtained by answering the eighth supplementary research question, which was mentioned above.

This study also aims to contribute to the body of knowledge related to the evaluation of the performance of quantitative funds by introducing some theoretical considerations pertaining to the issue-related definitions and nomenclature proposed in the foregoing studies. The aim of these theoretical considerations is to verify whether there is a consensus among researchers when it comes to defining quantitative, qualitative, and hybrid funds and when it comes to the issue-related nomenclature they apply. In the case of the lack of uniformity in the preceding publications, this thesis will make an attempt to propose some universal nomenclature and definitions. Conclusions drawn on the basis of the literature review should enable to answer the question of which features make an investment fund a real quantitative fund.

Research sample and methodology

For the purpose of this study, data pertaining to investment funds have been retrieved from the Thomson Reuters Eikon database. The research period began on 1st January 2000 and ended on 31st December 2020. The research sample includes all live and dead funds as of 15th January 2021, which were classified as absolute return funds, equity funds, hedge funds, and mixed asset funds according to the Lipper Global Classification scheme. A total number of retrieved investment funds was 392 089. Nevertheless, 97 001 of them were dropped due to missing data and additional assumptions made. Hence, a basic research sample consisted of 295 088 investment funds. They were grouped by the applied strategy according to the Lipper Global Classification scheme into four groups, namely absolute return funds, equity funds, hedge funds, and mixed asset funds. Moreover, they were also grouped by the region of a primary investment focus, taking into account The United Nations geo-scheme. However, in a detailed study, only four most numerous groups were examined, namely, funds primarily investing in Eastern Asia, Northern America, Northern Europe, and Western Europe.

This study had a comparative character. Thus, it was necessary to distinguish the groups of quantitative and qualitative funds. Most financial databases did not provide such a classification. They did not even provide any similar one. Hence, similarly to most of the foregoing studies on the performance of quantitative funds, this study had to deal with the problem of the research sample split into quantitative and qualitative groups. Some issue-related studies utilized a word-search method, which consisted in searching for specific words related to quantitative portfolio management in the description of fund operations (Chincarini, 2014; Harvey et al., 2017). If a given word was found in the description of fund operations, a fund was classified as a quantitative one. Otherwise, it was classified as a qualitative one. Some researchers declared that in order to gain more objectivity, they applied some more sophisticated split methods based on machine learning classification algorithms (Abis, 2018; Chuang & Kuan, 2018). In order to retrieve a training sample, Abis (2018) classified a part of the whole research sample personally. In the case of Chuang and Kuan (2018), some fund categories were already divided in the database and the researchers used them as training samples. The study conducted for the needs of this thesis follows the fund classification methodology proposed by Harvey et al. (2017).

A basic sample of 295 088 investment funds did not constitute the final research sample. Final research samples were selected in each of the three parts of the study separately due to the application of the rolling window method with additional requirements pertaining to a number of required observations in the windows. In order to ensure that this study had a clear structure, it was divided into three parts:

1. Weak-form informational efficiency study
2. Performance study with the use of the relative measures of portfolio performance, as well as raw and excess returns
3. Performance study with the use of econometric models

Supplementing a study on the performance of investment funds with a study on the features of their returns in the context of the weak-form informational efficiency is not that common. Nevertheless, this is not a completely new case. A similar approach was applied, for instance, by Zamojska (2012). The first part of the study verifies the H2 hypothesis and aims to answer the question of whether quantitative funds are more weak-form informationally efficient than qualitative funds. In order to do this, the first part of the study applies the tests for the martingale difference hypothesis (MDH) and normality tests. As far as the MDH tests are concerned, two tests were applied, namely the automatic Portmanteau test for serial correlation proposed by Escanciano and Lobato (2009), as well as the wild bootstrapped automatic variance ratio test under conditional heteroskedasticity proposed by Kim (2009) and constituting the modification of the automatic variance ratio test proposed by (Choi, 1999). When it comes to normality tests, the Lilliefors and D'Agostino-Pearson tests were applied. As opposed to the abovementioned MDH tests, tests for normality are considered strict random walk tests. The normality tests are conducted not only to verify the weak-form informational efficiency, but also to check if the application of some performance measures is justified, as some performance measures require the normality of the distribution of returns.

All calculations in the first part of the study were performed for the monthly returns of investment funds using a rolling window methodology. The tests were conducted for the 60-month windows of the monthly logarithmic returns of net asset values (hereinafter NAV) at the end of each month, rolled by 12 months (the next window began 12 months from the beginning of the previous window). A test was run only if, in a given window, a fund had at least 90% of a maximum number of observations, i.e., a required minimum number of observations to run a test was 54 (a maximum number of observations was 60).

Both the second and third part of the study verify the main research hypothesis H1 and aim to answer the question of whether the performance of quantitative funds is higher than the performance of qualitative funds. They also verify a supplementary research hypothesis H3 and aim to answer the question of whether quantitative funds perform better than qualitative funds in periods of low weak-form informational efficiency of equity markets. However, they do this with the use of different methods. The second part of the study applies the relative measures of portfolio performance, as well as raw and excess returns. Eleven measures applied come from the five groups of portfolio performance measures, such as unadjusted returns, classic measures based on the CAPM model, performance measures based on value at risk, lower partial moments, and maximum drawdown. This division of measures was based on divisions proposed by Aldridge (2010) and Bacon (2008). The second part of the study also applies a rolling window method with the same parameters as in the first part of the study.

The third part of the study applies two modified econometric models, namely, a modified Capital Asset Pricing Model (CAPM) and a modified Treynor-Mazuy Model (TM). The aforementioned modifications aim to capture differences between quantitative and qualitative funds in terms of selectivity and market-timing skills, as well as systematic risk. Studies dedicated to portfolio performance evaluation focus especially on two basic skills of a portfolio manager, namely selectivity and market timing. A portfolio manager using selectivity skills indicates which financial instruments are overvalued and undervalued. Selectivity is related to portfolio diversification that aims to reduce specific risk. Market timing refers to the ability to forecast market movements, which aims to choose a right moment for the conclusion of a transaction (Zamojska, 2012). The models were also estimated with the use of the rolling window method. However, its parameters changed. The changes pertained to the length of a window and a minimum percentage of observations in the window. The length of the window was changed to 84 months, and a minimum percentage of observations in a window was changed to 80%.

When it comes to applied research tools, calculations were performed mostly in RStudio, with the use of the R programming language. Moreover, Microsoft Excel was also used; however, in the minority of cases. The most important R packages used for the calculations were: nortest, vrtest, PerformanceAnalytics, and plm. Visualizations were mostly prepared with the use of the ggplot2 package.

Conclusions and limitations

A comparative analysis of performance and weak-form informational efficiency between quantitative and qualitative funds was performed for a few different samples, namely, a whole research sample, four samples distinguished in terms of strategy, and four most numerous samples distinguished in terms of the region of a primary investment focus. As far as differences in performance are concerned, quantitative funds managed to clearly outperform qualitative funds only in the case of the sample of absolute return funds. However, it did not hold in the case of market-timing skills. Quantitative funds had worse market-timing skills most of the time in this group. In none of the samples, quantitative funds had a clear advantage over qualitative funds in terms of both selectivity and market-timing skills. A clear advantage of qualitative funds over quantitative funds could be observed in the case of mixed asset funds. Nevertheless, it did not pertain to market-timing skills. In this group, quantitative funds had a clear advantage over qualitative funds in terms of market timing.

Regarding the results of the study on the weak-form informational efficiency of quantitative funds, similarly to the case of the performance study, the differences between quantitative and qualitative funds varied between the samples. When it comes to a whole sample and sub-samples distinguished in terms of the applied strategy, quantitative funds turned out to be slightly more efficient compared to qualitative funds. More significant differences in favour of quantitative funds could be observed in the case of hedge funds. Regarding sub-samples referring to the regions of a primary investment focus, quantitative funds were less efficient in the case of Eastern Asia and Northern America. In the case of the two remaining regions, quantitative funds were just slightly more efficient.

When it comes to the results of the study on the performance of quantitative funds in periods of low weak-form efficiency of equity markets, they also varied between the examined samples. In terms of market timing, quantitative funds appeared to take advantage of market inefficiencies in a better way compared to qualitative funds. However, when it comes to selectivity skills, quantitative funds managed mostly better only in the case of the samples of absolute return funds and funds primarily investing in Northern Europe.

The applied database allowed retrieving substantially larger research sample compared to the previous studies pertaining to the performance of quantitative funds. However, despite the application of a similar method of the classification of investment funds to Chincarini (2014) and Harvey et al. (2017), the share of quantitative funds was clearly lower compared to their studies. It may suggest that the database applied in this study may be inaccurate and insufficient to properly distinguish quantitative funds. However, the results of the studies by Chincarini (2014), Harvey et al. (2017), and even Chuang and Kuan (2018) allowed drawing quite similar conclusions. Future studies addressing the issue of the performance of quantitative funds may apply some different databases in order to find out whether their selection significantly affects conclusions drawn from the foregoing studies.

As was mentioned above, this study applied a method of the classification of investment funds similar to Chincarini (2014) and Harvey et al. (2017). The robustness of the results to the application of other split methods was not tested. Thus, the following issue-related studies may focus on finding more robust and more objective methods for distinguishing quantitative funds in financial databases.

The study conducted for the needs of this thesis focused on testing just one form of informational efficiency, namely the weak one. Future studies can examine quantitative funds also in terms of other forms of informational efficiency, such as the semi-strong and strong form. Another limitation of this study pertains to considering just one risk factor in applied econometric models, namely the equity market benchmark, which constitutes a systematic risk factor. It was some kind of compromise between the size and diversity of the research sample and the number of risk factors analysed. Collecting and processing such a large sample of investment funds was a huge challenge, especially in terms of technical aspects. Collecting other risk factors would constitute another great challenge. What is more, in many cases, it would be impossible due to the lack of access to relevant databases.

Thesis structure

This thesis is divided into eight chapters. Chapter 1 focuses on the review of the definitions of quantitative funds and qualitative funds. This chapter is also dedicated to the review of the relevant nomenclature proposed in the issue-related literature. Moreover, this chapter aims to distinguish characteristic features of quantitative and qualitative funds and standardise their definitions by proposing the new ones. Additionally, Chapter 1 discusses other important concepts related to quantitative funds. Chapter 2 shows the meaning of quantitative funds and other related concepts to financial markets. Chapter 3 constitutes a theoretical background for testing the efficiency of quant funds in the context of the weak-form informational market efficiency. Chapter 4 considers a theoretical background for the evaluation of the performance of quant funds. Chapter 5 presents a developed methodology for the research sample collection, a methodology for a study on the weak-form efficiency, and a methodology for a study on the performance of quant funds. Moreover, Chapter 5 discusses the structure of the research sample. This chapter also discusses the methodological approaches applied in the issue-related studies. Chapter 6 refers to a discussion of the results of the first part of the study, namely, the study on the weak-form informational efficiency of quantitative funds. Chapter 7 refers to a discussion of the results of the second part of the study, namely, the performance study with the use of the relative measures of portfolio performance as well as raw and excess returns. Chapter 8 refers to a discussion of the results of the third part of the study, namely, the performance study with the use of econometric models. This dissertation is concluded in the Ending remarks section.

1. The concept of a quantitative fund

A relatively new concept of quantitative investment funds, also called quant or systematic funds, undoubtedly gained much more attention in the financial media than among the academic researchers. Nevertheless, it still requires an in-depth study and clarifications, even when it comes to such basics as definitions and nomenclature. This chapter focuses on the review of the definitions of quantitative funds and their counterparties, commonly called qualitative funds, or, even more often, fundamental or discretionary funds. The goal of this chapter is to verify whether there is a consensus among researchers when it comes to defining quantitative and qualitative funds and when it comes to the issue-related nomenclature they apply. In the case of the lack of uniformity in the foregoing publications, this chapter will make an attempt to propose some universal nomenclature and definitions. Generally, conclusions should enable to answer the question, which features make an investment fund a real quant fund. The significance of the differences between quantitative and qualitative funds will allow to answer a question as to whether such a distinction is valuable and necessary at all. Taking into account that the world is not black and white, this chapter will also try to answer the question, if the researchers managed to distinguish and define a hybrid fund, combining characteristic features of both quantitative and qualitative funds.

This chapter does not limit itself just to the analysis of the definitions of quantitative, qualitative, and hybrid funds, but also clarifies some other terms that appear in studies and discussions pertaining to quantitative funds, such as quantitative portfolio management, quantitative trading, algorithmic trading, and high-frequency trading. This chapter also aims to demystify some misconceptions about the terms important from the point of view of this thesis.

Fulfilment of the objectives of this chapter is important due to empirical study and the need to make a personal classification of quantitative and qualitative funds retrieved from the applied database, which does not provide such a classification. This is a problem that occurs in most financial databases. Only knowledge of the substance of each fund type will allow to distinguish them properly and verify all stated research hypotheses.

1.1. The definitions of quantitative funds proposed in issue-related studies

Chincarini (2014) made an attempt to distinguish two subsamples of funds, namely, quantitative (quant) and qualitative (qual) funds (as he called them) out of the sample of hedge funds collected from the Hedge Fund Research (HFR) database. According to Chincarini (2014), a quantitative fund is the one that applies quantitative portfolio management techniques in the sense of Chincarini and Kim (2006), who proposed a division of portfolio management styles into quantitative and qualitative styles. According to Chincarini and Kim (2006), investment decisions of a quantitative portfolio manager are based mostly on a quantitative analysis, as opposed to a qualitative portfolio manager, whose investment decisions are based mostly on a qualitative analysis (these terms will be clarified in more detail in this section). A typical qualitative management style does not apply any mathematical or computer models.

Almost always a qualitative management is active, which means that the qualitative managers try to outperform the market by selecting undervalued or overvalued financial instruments. A selection of assets by qualitative managers is based primarily on their own judgement and intuition, and the data they collect is filtered with informal calculations. The data they use come from financial statements, financial ratios, research reports, or interviews with company personnel.

An opposite portfolio management style to a qualitative one is a quantitative portfolio management, which is much less concerned with intuition and intangibles but rooted in statistics and mathematics. Information collected by quantitative managers is filtered statistically and mathematically. Quantitative managers make financial decisions based on the indications of the quantitative models using relevant financial data and quantifiable information. While a qualitative approach to portfolio management is mostly related to active portfolio management, a quantitative approach to portfolio management is successfully applied in both active and passive portfolio management. Qualitative portfolio management is much more associated with great individuals, while quantitative portfolio management is much more associated with great institutions. One of the most important features of quantitative portfolio management is that it is usually supported by a well-structured and disciplined investment process.

A brief definition of a quantitative fund proposed by Guo, Lai, Shek, and Wong (2017) states that it is an investment fund, in which investment decisions are not made with the use of a human judgement, but instead with the use of models and computing machinery. Similarly to Chincarini and Kim (2006), also Guo et al. (2017) distinguished two contrary approaches to portfolio management, i.e., qualitative (or discretionary) and quantitative (or systematic) approach. According to their brief descriptions of the approaches, in a qualitative strategy investment decisions are made by human managers and in a quantitative strategy investment decisions are made by a computerized system instead.

Chincarini (2014) distinguishes the following reasons for the prevalence of quantitative portfolio management and its adoption even by qualitative managers:

- a rapid development of knowledge and tools pertaining to quantitative assessment of financial markets;
- advancement in technology, which allows for efficient quantitative examination of financial markets;
- demand from institutional investors for a structured investment process;
- some arguments saying that quantitative disciplined process may generate higher returns.

Chincarini and Kim (2006) propose the following advantages of quantitative portfolio management over qualitative portfolio management:

- investment decisions of a qualitative portfolio manager can be affected by some behavioural biases. In the case of quantitative portfolio management, the model determines investment decisions, thus, the impact of a human factor is minimised. Hence, quantitative portfolio management supports objectivity of the investment process and its transparency as the investment process can be introduced to investors;

- the state-of-the-art tolls used by the quantitative portfolio managers allow for a fast analysis of large amounts of data, which is impossible to qualitative managers;
- the quantitative investment process is replicable, easy to document, and present to investors. Moreover, it is easy to backtest a quantitative investment strategy on historical data and different securities;
- once a quantitative investment process is in place, the cost of portfolio management becomes lower and lower compared to a qualitative portfolio management;
- the state-of-the-art tolls used by quantitative portfolio managers allow for measuring and controlling a risk in a better way compared to qualitative portfolio managers.

The disadvantages of quantitative portfolio management in comparison to qualitative portfolio management proposed by Chincarini and Kim (2006) are as follows:

- in some cases, it is difficult to use qualitative information in the quantitative model due to problems with translation of qualitative inputs into quantitative data;
- quantitative models are heavily based on historical data. Moreover, models backtested on historical data may not be successful in the future as the historical relationships may not continue;
- quantitative managers use data mining to find some statistically significant relationships out of many tested on the historical data. Models built with the use of such relationships are likely to fail when facing future data;
- due to the development of quantitative portfolio management strategies based on historical data, quantitative strategies can slowly react to changing market conditions. Due to this, new and unprecedented market conditions can also be misinterpreted. This disadvantage of quants is also especially emphasized by Khandani and Lo (2011) and Abis (2018).

The aforementioned advantages and disadvantages of a quantitative portfolio management in comparison to a qualitative portfolio management proposed by Chincarini and Kim (2006) are summarised in Table 1.1.

Advantages		
Portfolio management type / Criteria	Quantitative	Qualitative
Objectivity of investment decisions	High	Low
Vulnerability to behavioural errors	Low	High
Efficiency of data processing (breadth)	High	Low
Replicability of investment strategy	High	Low

Costs of portfolio management	Low	High
Measuring and controlling the risk	High	Low
Disadvantages		
Criteria / Portfolio management type	Quantitative	Qualitative
Usage of qualitative information	Low	High
Historical data reliance	High	Low
Susceptibility to bad practices related to data mining	High	Low
Reaction to changing economic conditions	Low	High

Tab. 1.1. The advantages and disadvantages of quantitative and qualitative fund management. Source: Chincarini and Kim (2006)

Chincarini and Kim (2006) propose that qualitative management is sometimes mistakenly called fundamental management, since fundamentals are also used by quantitative managers. This statement is shared by Qian, Hua, and Sorensen (2007), who propose that it is inappropriate to contrast quantitative and fundamental management, as fundamental managers also use quantitative models and develop investment processes. Nevertheless, they do not indicate any term that would contrast with quantitative management. According to Chincarini and Kim (2006), a unique feature of qualitative management is focusing on intangibles in the process of making investment decisions, not on models. In addition, qualitative funds are based on the skills and intuition of their managers.

Ozair and Royal (2014) noticed that Fabozzi, Focardi, and Jonas (2008) made a distinction between quantitative and fundamental or traditional investment process, although the definitions of these contrary groups were in line with the definitions of quantitative and qualitative investment processes commonly shared in the academic literature. They defined a quantitative investment process as one in which computer-driven models generate quantitative outputs that constitute the basis for making investment decisions. In the fundamental investment process, instead, decisions are based on the judgement of the human asset manager. Thus, in this case, the definitions were similar but the terms were misleading. A similar issue appears in the studies by Parvez and Sudhir (2005), and Thurston (2011). These papers will be discussed further in this section.

Ozair and Royal (2014) suggest that the term 'fundamental' may be misleading when referring to portfolio management because:

- fundamentals do not constitute the only basis for all human investment processes, where technical analysis can be such an example;
- fundamental factors are used in most quantitative models.

Ozair and Royal (2014) suggest that the most appropriate terms for these two contrary methods would be 'automated' vs. 'judgmental', however, 'quantitative' vs. 'fundamental' remain commonly used terms. Fabozzi et al. (2008) are of the same view. This suggests that researchers consider the question 'how the investment decision is made, by a human or a computer?' a main criterion deciding to which group a given portfolio management style should be assigned, i.e., to a quantitative or qualitative group. According to Narang (2013), a key determinant separating a quantitative approach from a discretionary one is whether decisions on selection and sizing of portfolio positions are systematic (predefined and automated; nevertheless, still allowing for some emergency overrides) or discretionary (relying on human skills and intuition).

In the process of classifying funds as quantitative or qualitative, Chincarini (2014) searched for some specific terms in the names and descriptions of fund categories. Once a specific term appeared in the name or description of the fund category, a fund was classified as a quantitative or a qualitative one. The issue of funds classification as quantitative or qualitative will be discussed in more detail in Chapter 5. Chincarini (2014) classified a fund as quantitative when a term 'systematic' appeared in its category description or a category name. On the other hand, when the term 'discretionary' appeared in the description of the fund category or in the category name, a fund was classified as qualitative. However, the definitions of these terms are in vain to find in Chincarini (2014) and Chincarini and Kim (2006). These terms are crucial in the study by Harvey et al. (2017), which compares the performance and the risk exposures of funds managed systematically and discretionarily (as they call it). Harvey et al. (2017) follow the definitions of systematic and discretionary funds provided in the Hedge Fund Research database for Macro Systematic Diversified and Macro Discretionary Thematic subcategories. Harvey et al. (2017) propose that in the systematic funds, investment decisions are rule-based and implemented by a computer, with no or just a little influence of individuals. However, the Hedge Fund Research description of the Macro Systematic Diversified subcategory does not say that investment decisions have to be executed by computers. On the other hand, in discretionary funds, data are interpreted and investment decisions are made using human skills, by individuals or a group of individuals.

Harvey et al. (2017) refer to Chincarini (2014) and suggest that their fund classification (systematic vs. discretionary) is much different from the fund classification of Chincarini (2014) (quantitative vs. qualitative), as both systematic and discretionary funds apply some quantitative techniques to a lesser or greater extent. Harvey et al. (2017) mention that the word 'quantitative' occurred only 1.7 times more often in descriptions of funds from the Macro Systematic Diversified subcategory than it did in descriptions of funds from the Macro Discretionary Thematic subcategory. An inconsistency can be noticed here since Chincarini (2014) considered quantitative funds as systematic and qualitative funds as discretionary, as mentioned before. Nevertheless, to some extent it was already explained by Chincarini (2014), who proposed that most funds were neither strictly systematic nor qualitative, and despite that, an attempt was made to distinguish two types of funds, which apply more quantitative techniques (quantitative funds) and more discretionary techniques (qualitative funds). The aim was to learn about the relative importance of quantitative techniques. The definitions of quantitative and qualitative portfolio management proposed by Chincarini and Kim (2006) (on which Chincarini (2014) based his own selection of funds) pertained to strictly quantitative and qualitative funds, though in practice these two approaches to portfolio management are often mixed.

Chincarini and Kim (2006) perceive quantitative and qualitative approaches to portfolio management binarily, as portrayed in Figure 1.1. below. They do not mention any mixed approaches, which are commonly applied in practice. Nevertheless, to some extent, it is understandable as it can be very difficult to estimate the probability of being a pure quantitative or qualitative fund. Investment funds usually admit to apply only one of the two approaches discussed. Thus, in empirical studies related to the issue of performance of quantitative funds, researchers distinguish mainly only two groups of funds. Their approaches to dealing with this problem are discussed in further detail in this chapter.

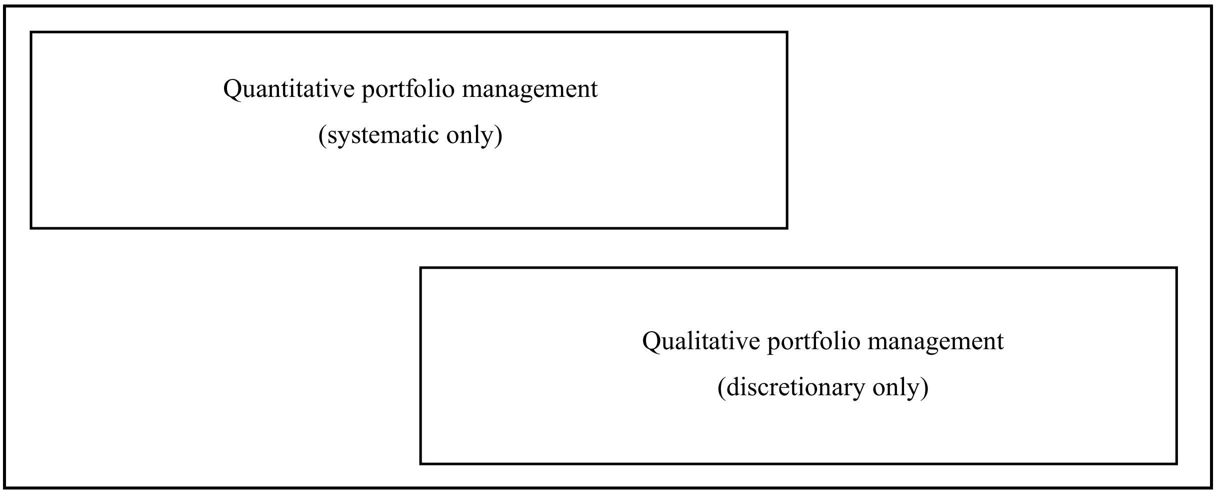

Fig. 1.1. A binary division of portfolio management into quantitative and qualitative portfolio management proposed by Chincarini and Kim (2006). Source: Author's own study based on Chincarini and Kim (2006)

Table 1.2. presents the summary of the features of strictly quantitative and qualitative portfolio management styles proposed by Chincarini and Kim (2006).

Portfolio management style / Criteria	Quantitative	Qualitative
Investment process	Formal, rooted in mathematics and statistics, model-driven, systematic	Intuitive, concerned with intangibles, discretionary
Data	Large sets of numerical data and quantifiable information, filtered mathematically	Small sets of numerical data, quantifiable and hard to quantify information, filtered with informal calculations
Portfolio management style	Both active and passive	Mostly active

Tab. 1.2. Main features of strictly quantitative and qualitative portfolio management styles. Source: Author's own study based on Chincarini and Kim (2006)

Ozair and Royal (2014) propose that quantitative and qualitative investment processes should be combined, as a qualitative approach to investment is still needed due to difficulties in quantification and analysis of some qualitative information, like information pertaining to human capital. Combining these two methods provides a holistic picture of the investment process. The authors focus on the inability of the quantitative portfolio management approach to conduct systematic analyses of management quality and suggest supplementing it with rigorous qualitative research considering change in management themes, human capital, and special events. A particular emphasis is put on the concept of human capital defined as a system of peer management of an organisation, observable and comparable across sectors and time, having a great impact on organisation performance, and being difficult to measure and include in a quantitative investment process.

According to Ozair and Royal (2014), financial professionals share a common opinion that quantitative investment process is reserved for the most technically advanced funds, in which the investment process is model- and computer-based. They also propose that in a pure quantitative fund, investment decisions are determined by models rather than by humans. However, they emphasize that there are also hybrid approaches used where the indications of the models are supported or confirmed by a judgement of a portfolio manager, as shown in Figure 1.2.

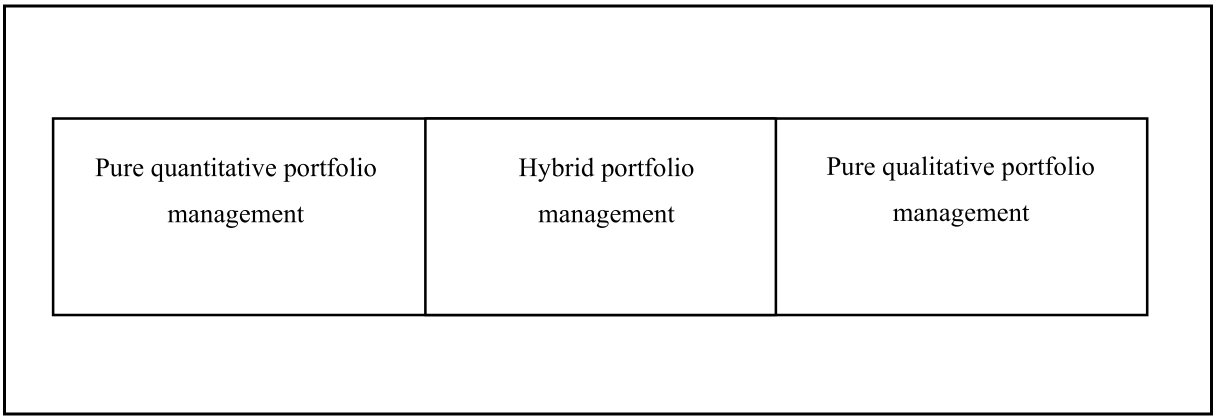

Fig. 1.2. Division of portfolio management methods proposed by Ozair and Royal (2014). Source: Author's own study based on Ozair and Royal (2014)

Ozair and Royal (2014) suggest that the automatization of a quantitative process is mostly dependent on the investment time horizon. Due to the limits of a human, along with a decrease of a holding period, it is more likely that the process becomes more automatic. The automatic process is better suited to algorithmic trading, especially to its subgroup, namely high-frequency trading (these concepts will be clarified further in this chapter). In the case of a pure quantitative portfolio management process, a human judgement may appear only in the case of:

- algorithm development, programming and testing;
- making a decision on the algorithm execution (nevertheless, cases of the system override by a human should appear only in emergency situations).

Ozair and Royal (2014) also distinct a concept of a model-driven portfolio management process, which consists of three main elements i.e., input system, forecasting engine, and portfolio construction engine. Human judgement can be applied to all the aforementioned elements, mainly as a control function that checks whether the system's operations make sense. The same elements of the investment process have been mentioned by Guo et al. (2017) as key components of the investment process in a quantitative fund:

- input system – provides all necessary inputs including data and rules;
- forecasting engine – estimates future prices and returns as well as evaluates risk;
- portfolio construction engine – generates recommended portfolios using optimization and heuristics.

As mentioned above, most issue-related studies compare only two groups of funds, i.e., quantitative and qualitative funds. The only exception known to the author of this thesis is a study by Lin (2019), questioning criticism towards the quantitative portfolio management and comparing the performance of over 240 active equity Australian and Global equity managers divided into 3 groups, i.e., quantitative, fundamental, and combined (quantamental) funds. The separation of 3 groups in the study by Lin (2019) was manageable due to the eVestment database, in which portfolio managers directly self-report the applied portfolio management style.

A term 'quantamental' is a combination of words the 'quantitative' and 'fundamental'. It is commonly used in the literature for portfolio management strategies that combine quantitative and qualitative techniques. It is a very broad term, as there are many ways to combine these two techniques. For instance, López de Prado (2018) defines quantamental approach as portfolio management techniques combining mathematical forecasts with human guesses or combining human expertise with quantitative methods. Arslanian and Fisher (2019) define quantamental approach as an investing style merging fundamental and quantitative techniques, focused on developing a symbiotic relationship between the quantitative tools and fund manager, as well as seeking to combine complementary strengths of both approaches. Arslanian and Fisher (2019) compare the quantamental approach to modern chess computers cooperating with human chess experts, consistently beating together both world's most advanced chess programs and human chess grandmasters. Also, López de Prado (2018) suggests that the quantamental approach may deliver the best results. Gray, Vogel, and Foulke (2015) propose that the quantamental approach seeks to unite human financial experts and models, using best features of both. According to Svetlova (2018), a quantamental approach combines a past-based and repeatable process of securities selection with a qualitative judgement bringing future prospects of securities and economies into the process. Svetlova (2018) proposes that in a pure form of the fundamental approach to portfolio management, it is believed that the best solution to the problem of promising investment opportunities identification, is to exercise human judgement. This approach is based on the qualitative processing of economic data. The quantitative approach to portfolio management instead applies statistical and mathematical procedures to select promising securities. This approach aims to identify securities selection criteria based historical data. Fabozzi et al. (2008) proposed that a ‘hybrid’ investment management process (they do not apply the name ‘quantamental’) is a combination of fundamental and quantitative processes. A fundamental process is defined as one performed by a human asset manager applying information and judgment. A quantitative process is defined as one in which quantitative outputs generated by computer-driven models (following fixed rules) constitute a basis for making investment decisions.

Guida (2019) suggests that one of the biggest challenges in developing quantamental strategies is reconciling ‘depth’ and ‘breadth’. An in-depth study of individual securities is characteristic for fundamental analysts and managers (as he called them). Breadth i.e., the number of securities held in portfolio is a domain of quantitative managers. According to Grinold’s fundamental law of active management (Grinold, 1989; cited in Guida, 2019), both ‘depth’ and ‘breadth’ determine the manager’s information ratio (IR), which constitutes a measure of the manager’s risk-adjusted active return:

$$IR = IC \times \sqrt{N} \quad 1.1.$$

where:
IC – a measure of skill; information coefficient, which constitutes a relation between the predictions of a manager and subsequent realized returns;
N – a measure of breadth; independent bets.

Quantitative portfolio managers focus on breadth (N). Their strategies can be replicated and applied for many assets. However, their return from particular trades is rarely high. In quantitative strategies, the bets are rather often. Many of them can be wrong, but on average the quant strategies can still be profitable. Fundamental managers focus on the information coefficient (IC). An in-depth research conducted by fundamental analysts aims at generating high return from a particular trade. Nevertheless, the results of their analysis can rarely be used to make an investment decision in relation to other securities.

Combining quantitative and qualitative techniques may deliver different quantamental forms. When proposing some possible quantamental outcomes, progressively adopting more quantitative techniques, Guida (2019) focused on the adoption of quantitative techniques among fundamental analysts and portfolio managers:

- collecting sophisticated data delivering deeper insights about an individual company, without necessarily increasing breath;
- systems delivering information about some market trends or suggesting trade ideas;
- systems creating rankings and scores on securities.

Fabozzi et al. (2008) propose the following ways in which quantitative and qualitative approaches can be combined:

- a human manager overseeing a quantitative process, intervening only in some exceptional cases;

- models providing information to human managers like screening and other decision-support systems, which narrow search and put some constraints on portfolio construction;
- models incorporating human judgement (for instance, using Bayesian priors) and changing risk parameters according to human judgement;
- overriding model with a human decision.

Narang (2013) used a different name for the approach that combines systematic and discretionary strategies, namely he called it ‘quasi-quant’. The examples of the approach proposed by Narang (2013) are as follows:

- delivering a smaller and easier to manage discretionarily list of potential investment opportunities by an automated screening system;
- investment opportunities are selected by humans, and computers are used to optimize and implement portfolios, as well as to manage the risk;
- the computer selects some investment opportunities and then the human decides on the allocation among the trades selected by the computer.

Considering quantitative and fundamental equity management, Fabozzi and Markowitz (2011) suggest that combining these two approaches can be very beneficial as they are quite complementary and can provide a well-rounded and robust picture of a single company or a portfolio. Fabozzi and Markowitz (2011) propose that a fundamental approach focuses on individual securities and covers a narrow group of them to make an in-depth individual analysis feasible. Due to an in-depth study of individual securities, fundamental managers have greater conviction in taking larger positions. Risk and performance are managed more at the individual security level and the attention is paid to future prospects of a security. On the other hand, the quantitative approach focuses on the characteristics of the securities that can affect the investment return and covers broad samples of the securities trying to determine the factors that separate them. Quantitative managers take smaller positions in order to spread their bets across a larger sample of securities. Risk and performance are managed more at the portfolio level, and attention is paid to historical data. The features mentioned above for quantitative and fundamental portfolio management proposed by Fabozzi and Markowitz (2011) are summarized in Table 1.3.

Approach / Attribute	Quantitative	Fundamental
Primary focus	Securities characteristics	Individual securities
Investment decision	Disciplined (model-based)	Qualitative (manager’s assessment)
Manager’s role	Scientist	Journalist
Portfolio size	Large	Small
Position size	Small	Large
Bets concentration	Small (bets are spread)	Large (high conviction)

Risk perspective	Portfolio level	Security level
Performance perspective	Portfolio level	Security level
Time dimension focus	Past (historical data)	Future (future prospects)

Tab. 1.3. Features of quantitative and fundamental portfolio management proposed by Fabozzi and Markowitz (2011). Source: Author's own study based on Fabozzi and Markowitz (2011)

Fabozzi and Markowitz (2011) propose that the quantamental approach may deliver the following benefits:

- a broad analysis of a large group of securities, aiming at selecting a subset of the best securities, followed by an in-depth analysis of individual securities in the selected subset;
- a scientific and repeatable approach to analysing large amounts of data complemented by personal judgement at the level of an individual security;
- a detailed review of the historical data aiming to find out what worked in the past, combined with a review of the future prospects of a security;
- evaluation of the risk at the level of an individual security and a whole portfolio;
- evaluation of performance at particular levels of a portfolio.

The benefits of a quantamental approach mentioned above are summarized in Figure 1.3.

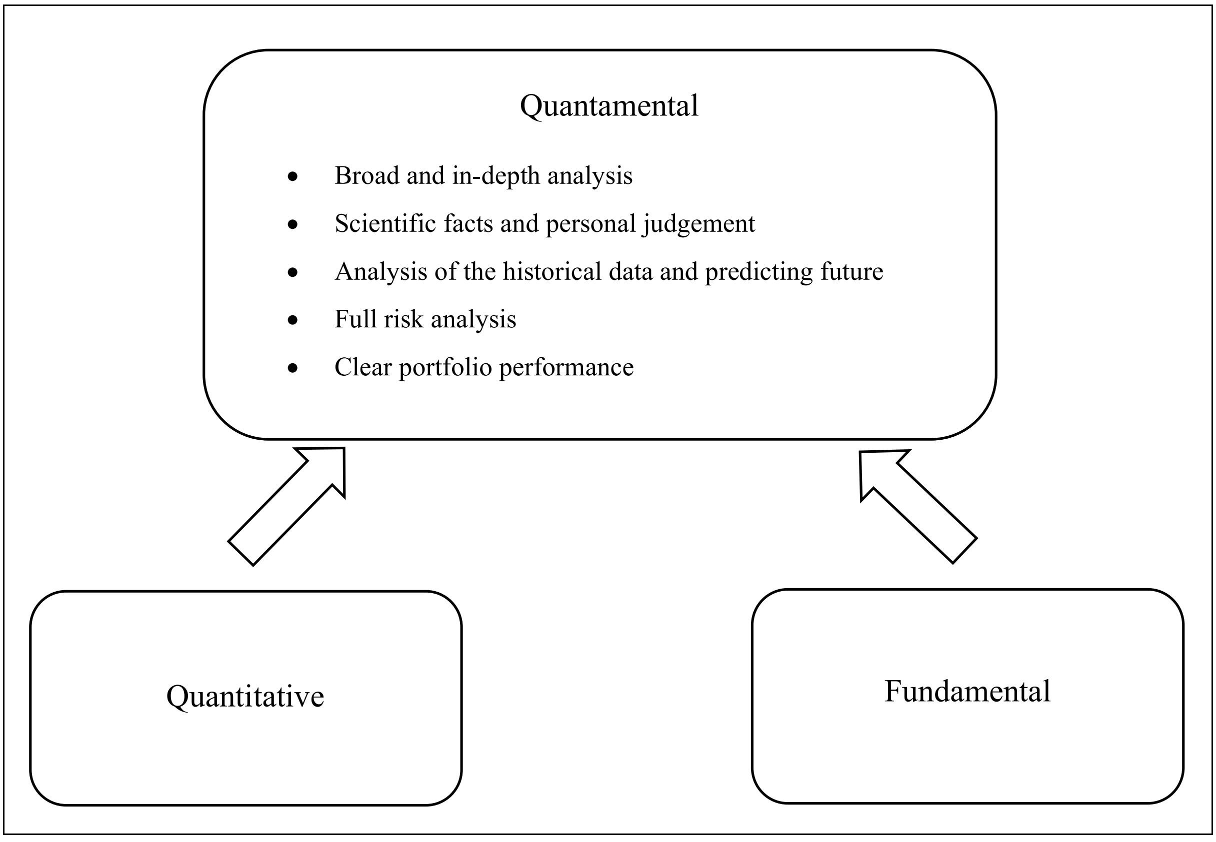

Fig. 1.3. Benefits of the quantamental approach proposed by Fabozzi and Markowitz (2011). Source: Author's own study based on Fabozzi and Markowitz (2011)

According to Jansen (2020), a quantamental approach to portfolio management has been adopted by discretionary funds (as he calls them) as a result of spread of the algorithmic strategies from the core hedge fund industry. He defines systematic portfolio management as a repeatable and data-driven approach that relies on algorithms looking for investment opportunities across a broad range of securities. A contrary approach, namely, discretionary portfolio management, focuses on an in-depth fundamental analysis of a narrow range of securities.

Most financial databases do not provide any classifications that divide universes of investment funds into quantitative, qualitative, and hybrid categories. Due to this problem, most of the issue-related studies had to conduct their own allocation of funds. Additionally, in the majority of cases, information pertaining to individual investment funds does not allow to answer the question of whether a fund is purely quantitative, qualitative, or whether it combines features of both aforementioned groups. Thus, most of the foregoing studies raising an issue of quantitative funds divided the examined universes into two groups only, namely, into a quantitative group and a qualitative group. This approach constitutes indeed a certain type of simplification; nevertheless, it still allows to learn about the relative importance of quantitative techniques. It is related to the assumption that investment funds classified as quantitative funds apply more quantitative techniques than investment funds classified as qualitative funds.

Abis (2018) made an attempt to select two contrary groups of funds out of the US equity mutual funds universe, i.e., quantitative and discretionary funds (as she called them). Abis (2018) defined quantitative funds as funds that utilize computer-driven models. The models analyse large datasets with the use of fixed rules and generate signals that constitute a basis for making investment decisions. The definition of discretionary funds proposed by Abis (2018) states that their investment process is based mostly on the intuitive judgement of the asset manager. The aforementioned definitions of the contrary approaches to portfolio management proposed by Abis are very similar to definitions proposed by Chincarini and Kim (2006) and Harvey et al. (2017), although their nomenclature is different. The definition of a quantitative fund by Abis (2018) corresponds to the definition of a quantitative portfolio management by Chincarini and Kim (2006) and a systematic fund by Harvey et al. (2017). The definition of a discretionary fund by Abis (2018) corresponds to the definition of a qualitative portfolio management by Chincarini and Kim (2006) and a discretionary fund by Harvey et al. (2017).

Chuang and Kuan (2018) aimed to separate sub-samples of systematic and discretionary funds (as they call them) out of the sample of investment funds included in the Hedge Fund Research database under Equity Hedge and Macro category (following Harvey et al. (2017)). They tried to do this in as much objective way as possible. Exploiting funds categorization provided by the HFR database, they used Systematic Diversified and Discretionary Thematic subcategories to train several machine learning algorithms and test their accuracy. Then, using the most accurate machine learning algorithm, namely a random forest, they separated 9,408 investment funds. The fund classification performed by Chuang and Kuan (2018) will be discussed further in detail in Chapter 5.

Chuang and Kuan (2018) define systematic funds as investment funds in which investment decisions are mainly based on signals generated by quantitative models without human intervention. Discretionary funds are instead defined as investment funds, in which investment decisions are based on the experience and professional skills of the portfolio manager. Chuang and Kuan (2018) mention that their classification is in line with the classification of the Hedge Fund Research and is similar to classifications proposed by Harvey et al. (2017), Chincarini (2014) and Abis (2018).

Parvez and Sudhir (2005) divided the enhanced index equity funds available in the Morningstar on Disc database into two subcategories, namely, quantitative and fundamental funds (as they called them). Researchers defined quantitative funds as investment funds based primarily on computer models in the securities selection process. Fundamental funds were defined as investment funds that base their securities selection process on a detailed fundamental analysis. According to Parvez and Sudhir (2005), the main thing that differentiates quantitative funds from fundamental ones is focusing on attractive characteristics and factors across many securities. Fundamental funds focus instead on individual securities and conduct detailed research at the level of individual assets.

Parvez and Sudhir (2005) analysed the prospectuses of funds, and only funds that claimed to follow an enhanced index strategy were included in the final sample. Then, they divided this sample into sub-samples of quantitative and fundamental funds. Funds were considered quantitative if they claimed to strictly follow a quantitative investment process. Other funds were classified as fundamental funds.

AQR (2017), more precisely, AQR Capital Management, a global investment management firm, notices that terms such as 'discretionary', 'fundamental' and 'stock-picking' are often used interchangeably with reference to the portfolio management technique applied by investment funds. The same refers to terms perceived as contrasting, such as 'systematic', 'quantitative' and 'rule-based'. The authors emphasize that it is correct to contrast systematic and discretionary approaches, but they are not the complete opposites as they may share some common features. For instance, both can be active and fundamentally oriented. They may use similar inputs and aim for similar goals, but with the use of different means.

AQR (2017) made an attempt to compare the performance of binarily divided subsamples of discretionary and systematic funds, selected from the universe of active equity funds included in the eVestment database. Unlike the other issue-related studies, AQR (2017) did not face the problem of the need to find a solution to separate discretionary and systematic funds. In the eVestment database, fund managers self-reported the applied approach. Although the eVestment database allowed fund managers to choose between 'quantitative' and 'fundamental' categories, AQR (2017) utilized the terms 'systematic' and 'discretionary', replacing the terms proposed by the eVestment database. Similarly as in the case of the other issue-related studies, AQR (2017) did not expect any category for a hybrid approach. The eVestment database was also used in the issue-related study by Lakonishok and Swaminathan (2010), as well as in the study by Lin (2019), who discussed criticism towards the performance of quantitative funds. Criticism towards the performance of quantitative funds was also discussed by Thurston (2011), who utilized data from the Russel database. The issue of criticism towards the performance of quantitative funds will be discussed further in this chapter.

AQR (2017) defined the systematic approach to portfolio management as one relying on computers in the process of identifying investment opportunities across numerous securities. A systematic process is repeatable and data-driven. Human discretion or judgement is used mostly just in the process of developing an investment strategy and risk control rules. A discretionary approach to portfolio management is based on the in-depth analysis of a less numerous sample of securities. Information that cannot be easily quantified plays a key role in this approach. Investment decision is supported by human intuition or judgement on a case-by-case basis.

1.1.1. The summary of discussed definitions of quantitative funds proposed in issue-related studies

The foregoing review of the definitions and nomenclature proposed in the issue-related studies suggests that there is no complete consensus on the question of defining quantitative funds. Furthermore, there is also no complete consensus on the issue-related nomenclature. The term ‘quantitative fund’ or ‘quant fund’ seems to be widely accepted and used in the media and among academics. However, considering that the answer to a question ‘is the investment process predefined and automated?’ is the most important criterion separating one group from another, the better names would be ‘automated’ vs. ‘judgemental’ (following Ozair and Royal (2014), as well as Fabozzi et al. (2008)) or ‘systematic’ vs. ‘discretionary’ (following Narang (2013)). However, due to the popularity of the term ‘quant fund’ and its approval among academics and professionals, the suggestion coming from the author of this thesis is to use exactly this name instead of others to avoid further vagueness. A proposed name for the contrary group is a ‘qualitative fund’, as the more popular name ‘fundamental fund’ could be very misleading, as discussed earlier in this section.

Taking into account common features of the reviewed definitions and the most important criterion distinguishing quantitative funds from qualitative ones, namely the answer to a question ‘is the investment process predefined and automated?’ the following brief definitions of quantitative, qualitative, and hybrid funds are proposed:

Fund type	Quantitative fund	Hybrid fund	Qualitative fund
Definition	A fund in which investment decisions are based on the indications of a predefined and automated investment process with none or a limited human intervention	A fund in which investment decisions are based on the cooperation of a predefined, automated investment process and human manager’s judgement	A fund in which investment decisions are made by a human manager’s judgement, relying on his skills and intuition

Tab. 1.4. Proposed definitions of quantitative, qualitative and hybrid funds. Source: Author’s own study

The three tables presented below gather the definitions discussed in this section which have been proposed in the issue-related studies. Table 1.5. presents definitions of quantitative and qualitative portfolio management styles. Table 1.6. presents definitions of quantitative and qualitative funds. Table 1.7. presents definitions of the hybrid management style. The tables also indicate the specific nomenclature applied by particular authors.

Definition of quantitative portfolio management (name proposed by a particular author)	Definition of qualitative portfolio management (name proposed by a particular author)	Author
(Quantitative) A quantitative portfolio management is much less concerned with intuition and intangibles, but rooted in statistics and mathematics. Information collected by quantitative managers is filtered statistically and mathematically. Quantitative managers make financial decisions based on the indications of the quantitative models using relevant financial data and quantifiable information. While a qualitative approach to portfolio management is mostly related to active portfolio management, a quantitative approach to portfolio management is successfully applied in both active and passive portfolio management. One of the most important features of quantitative portfolio management is that it is usually supported with a well-structured and disciplined investment process.	(Qualitative) A typical qualitative management style does not apply advanced mathematical or computer models. Almost always, qualitative management is active, which means that qualitative managers try to outperform the market by selecting undervalued or overvalued financial instruments. The securities selection of qualitative managers is based mainly on their own judgement and intuition, and the data they collect are filtered with informal calculations. Data they use come from financial statements, financial ratios, research reports, or interviews with company personnel.	Chincarini and Kim (2006)
(Quantitative / Systematic) In quantitative strategy, investment decisions are made by a computerized system instead.	(Qualitative / Discretionary) In qualitative strategy, investment decisions are made by human managers.	Guo et al. (2017)
(Systematic) Relying on computers in the process of the identification of the investment opportunities across numerous securities. Repeatable and data-driven. Human discretion or judgement is used mostly just in the process of developing investment strategy and risk control rules.	(Discretionary) Based on the in-depth analysis of a less numerous sample of securities. Information that cannot be easily quantified plays a key role in this approach. The investment decision is supported by human intuition or judgement on a case-by-case basis.	AQR (2017)

(Quantitative) Quantitative portfolio managers focus on breadth (N). Their strategies can be replicated and applied to many assets. Nevertheless, their return from particular trades is rarely high. In quantitative strategies, the bets are quite often. Many of them can be wrong, but on average the quant strategies can still be profitable.	(Fundamental) Fundamental managers focus on the information coefficient (IC). In-depth research conducted by fundamental analysts aims to generate high return from a particular trade. However, the results of their analysis can rarely be used to make an investment decision related to other securities.	Guida (2019)
(Quantitative) Quantitative approach focuses on securities' characteristics, which can affect investment return and covers broad samples of securities trying to determine which factors separate securities. Quantitative managers take smaller positions to spread their bets across a larger sample of securities. Risk and performance are managed more at the portfolio level, and attention is paid to historical data.	(Fundamental) The fundamental approach focuses on individual securities and covers a narrow group of them to make an in-depth, individual analysis feasible. Due to an in-depth study of the individual securities, fundamental managers have greater conviction in taking larger positions. Risk and performance are managed more at the individual security level and attention is paid to future prospects of the security.	Fabozzi and Markowitz (2011)
(Systematic) Systematic portfolio management is a repeatable and data-driven approach relying on algorithms, looking for investment opportunities across a broad range of securities.	(Discretionary) Discretionary portfolio management focuses on an in-depth fundamental analysis of a narrow range of securities.	Jansen (2020)
(Quantitative) Quantitative approach to portfolio management instead applies statistical and mathematical procedures to select promising securities. This approach aims to identify the securities selection criteria on the basis of historical data.	(Fundamental) In the pure form of the fundamental approach to portfolio management, it is believed that the best solution to the problem of identifying promising investment opportunities is to exercise human judgement. This approach is based on qualitative economic data processing.	Svetlova (2018)
(Quantitative) A quantitative process is defined as a one in which quantitative outputs generated by computer-driven models constitute a basis for making investment decisions.	(Fundamental / Traditional) A fundamental process is defined as a portfolio management process performed by a human asset manager applying information and judgment.	Fabozzi et al. (2008)

Tab. 1.5. Definitions of quantitative and qualitative portfolio management proposed in the reviewed studies, including specific names of portfolio management approaches applied by the authors. Source: Author's own study

Definition of a quantitative fund (name proposed by a particular author)	Definition of a qualitative fund (name proposed by a particular author)	Author
(Quantitative) An investment fund in which investment decisions are not made with the use of a human judgement, but instead with the use of models and computing machinery.	-	Guo et al. (2017)
(Systematic) In the systematic funds, investment decisions are rules-based and implemented by a computer, with no or just a little influence of the individuals.	(Discretionary) In the discretionary funds, data are interpreted and investment decisions are made using human skills, by individuals or a group of individuals.	Harvey et al. (2017)
(Quantitative) In a pure quantitative fund, investment decisions are determined by the models rather than by a human.	-	Ozair and Royal (2014)
(Quantitative) Utilize computer-driven models analysing large datasets with the use of fixed rules and generating signals, which constitute a basis for making investment decisions.	(Discretionary) Their investment process is mainly based on the intuitive judgement of the asset manager.	Abis (2018)
(Systematic) In which the investment decisions depend mostly on signals generated by the quantitative models without any human intervention.	(Discretionary) In which the investment decisions are based on experience and professional skills of the portfolio manager.	Chuang and Kuan (2018)
(Quantitative) Primarily relying on computer-based models in the securities selection process.	(Fundamental) Relying their securities selection process on detailed fundamental analysis.	Parvez and Sudhir (2005)

Tab. 1.6. Definitions of quantitative and qualitative funds proposed in the reviewed studies, including specific names of funds applied by the authors. Source: Author’s own study

Definition of a hybrid portfolio management	A proposed name of the approach	Autor
Portfolio management techniques combining mathematical forecasts with human guesses or combining human expertise with quantitative methods.	Quantamental	López de Prado (2018)
An investing style merging fundamental and quantitative techniques, focused on developing a symbiotic relationship between the quantitative tools and fund manager, as well as seeking to combine complementary strengths of both approaches.	Quantamental	Arslanian and Fisher (2019)
Quantamental approach seeks to unite human financial experts and models using best features of both.	Quantamental	Gray, Vogel, and Foulke (2015)
Quantamental approach combines a past-based and repeatable process of securities selection with a qualitative judgement bringing future prospects of securities and economies into the process.	Quantamental	Svetlova (2018)
A 'hybrid' investment management process (they do not apply the name 'quantamental') is a combination of fundamental and quantitative processes.	Hybrid	Fabozzi et al. (2008)

Tab. 1.7. Definitions of a hybrid portfolio management proposed in the reviewed studies, including specific names of this portfolio management approach applied by the authors. Source: Author's own study

1.2. A typical structure of a quantitative trading strategy

It is often alleged that a quantitative approach to portfolio management relies on difficult-to-understand 'black boxes'. According to Narang (2013), the origins of the term 'black box' are mysterious; nevertheless, its first known use was in a sci-fi serial *The Black Box* from 1915, in which a criminologist Sanford Quest solves crimes using self-invented devices placed inside a black box. Those who guessed the contents of the black box could count on cash prizes offered by a producer of the serial i.e., Universal Studios. A term 'black box', commonly used in science and finance, refers to any system fed with inputs and producing outputs whose inner processes are unknown or unknowable. Narang (2013) in his book, titled 'Inside the Black Box: A Simple Guide to Quantitative and High-Frequency Trading', aims to demystify quantitative trading and convince readers that, in fact, quantitative trading strategies are easier to understand than the human decision-making process, in which irrationality and caprice cannot be avoided. The quantitative trading strategy is what supposes to give the advantage over qualitative funds to quantitative funds. The verification of the main research hypothesis H1 will provide an answer to the question of whether the quantitative trading strategy provides quantitative funds with such an advantage. Narang (2013) tries to achieve his goals with an explanation of the components that form a typical structure of a quantitative trading strategy. A basic structure of a typical quant trading strategy is presented in Figure 1.4.

In a typical quant trading strategy, an alpha model, a risk model, and a transaction cost model feed into a portfolio construction model. The portfolio construction model interacts with the execution model. The purposes of a particular quantitative trading strategy components can be described as follows:

- alpha model – predicts future prices/quotes/returns of financial instruments;
- risk model – limits the exposure to factors that are likely to generate losses rather than gains;
- transaction cost model – determines costs of trades and answers a question, whether it makes sense to enter a transaction (expected costs can be higher than expected profits);
- portfolio construction model – determines the best portfolio to hold by balancing the trade-offs presented by the pursuit of profits (alpha model), risk limiting (risk model) and trading costs (transaction cost model);
- execution model – takes trades required by the portfolio construction model.

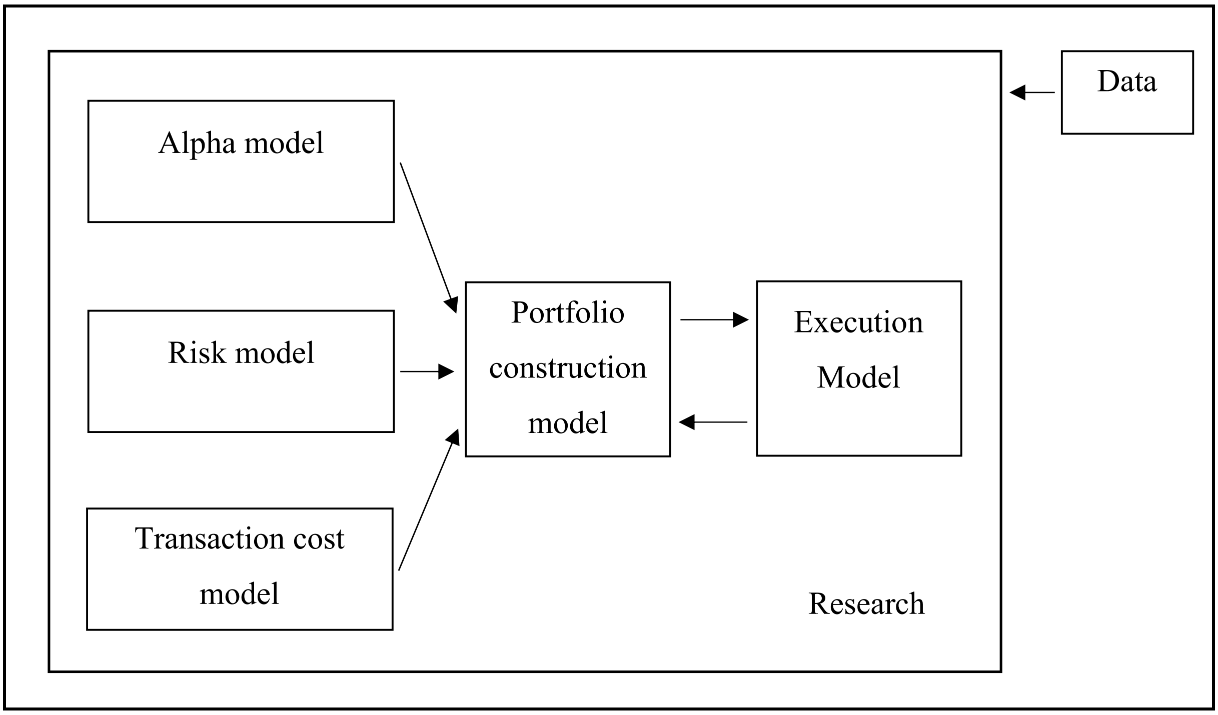

Fig. 1.4. A basic structure of a typical quant trading strategy. Source: Author's own study based on Narang (2013)

Regardless of whether the actual strategy is organised precisely in such a manner, the diagram presented in Figure 1.4. is universal as it captures various processes within a quantitative trading strategy. For example, the actual strategy may not include a transaction cost model, a portfolio construction model, or an execution model. Other strategies may combine components of the models or create more recursive connections among them.

The other two key elements of a quant trading strategy presented in Figure 1.4. are data and research. With reliable and accurate data, the quants can perform research in order to develop a trading strategy. The data constitute the necessary input, which is processed and affects the output. Research is conducted continuously, not only at the level of the development of quantitative trading strategy. During a research process fed with the market data, quants check if their ideas hold true over time. If they do, quants incorporate them into the quantitative trading strategy, constituting a disciplined approach to investing, taking out the emotions from it. Nevertheless, the importance of a human in the quant trading strategy is still great as a human develops it and can still override it. The issue of a human overlay in the quantitative approaches to portfolio management has been discussed for instance by Fabozzi, Foracrdi, and Jonas (2008).

Guo et al. (2017) propose five essential components of a quantitative trading strategy, i.e., data, analytics, models, optimization, and algorithms. The order of the aforementioned components is not random, as according to the authors, their order portrays their flow in the quantitative trading system. Analytics refers to the analysis of data as well as to the development of data-driven strategies. Models refer to developed data-driven strategies that connect data and investment decisions made. Algorithms are step-by-step procedures for computing the solutions of mathematical, data analysis, and optimization problems. The definition of an algorithm mentioned by the US Securities and Exchange Commission (SEC) (2020) states that, at the most general level, it is a deterministic, finite, and effective method that solves problems and whose implementation as a computer program is suitable. Algorithms can also be responsible for carrying out trades, namely, placing orders on the market. When algorithms carry out trades, we talk about algorithmic trading, a very popular term in the financial markets literature.

1.3. Algorithmic and high-frequency trading

Many researchers, institutions of various kinds, or even legislators have made an attempt to define algorithmic trading. For example, Article 3, paragraph 2b of the Polish Financial Instruments Trading Act (2005) defines algorithmic trading as the purchase and sale of financial instruments with the use of computer algorithms, which set individual parameters of purchase and sales orders of these instruments with none or a limited involvement of a human. This definition is in line with the one provided in Article 4, paragraph 1, point 39 of Directive 2014/65/EU of the European Parliament and of the Council of 15 May 2014 on Markets in Financial Instruments (co-called Directive MiFID II). The definitions of algorithmic trading provided in these two acts were additionally detailed by Article 18 of the Commission Delegated Regulation 2017/565 of 25 April 2016, according to which an algorithmic trading system operates with no or a limited human intervention, when for any order-execution optimisation process or any order or quote generation process, an automated algorithmic trading system applies predetermined parameters to make decisions at any stages of orders or quotes initiation, generation, routing, and execution. According to the Polish Financial Supervisory Authority, algorithmic trading refers to trading in financial markets using computer software applying algorithms, which automatically generate orders and transfer them to the transaction platform[1].

Moving onto the academic definitions, according to Guo et al. (2017) algorithmic trading refers to entering trade orders on electronic platforms with the use of algorithms executing trading strategies applying programs whose variables are the outputs of the quantitative trading strategy. Their five already-mentioned essential elements are: data, analytics, models, optimization, and algorithms. The authors also mention that the algorithmic trading (also referred to as algo trading or automated trading) is widely used by both, the buy-side (e.g., institutional traders, hedge funds, mutual funds) and the sell-side financial institutions (e.g., market makers, investment banks, hedge funds providing liquidity to the market). Kissell (2014) defines algorithmic trading (also automated, black box or robo trading) as a computerized execution of trades.

A common ground of the algorithmic trading definitions mentioned above is the execution of orders by algorithms without or with a limited human intervention. Thus, the question arises, whether a fund has to apply algorithmic trading in order to be considered quantitative? Most definitions of quantitative fund, quantitative portfolio management, and quantitative trading, mentioned in the previous sections of this chapter, suggest that quantitative funds do not have to apply algorithmic trading. The reviewed definitions stipulate that investment decisions must be made without or with limited human discretion. It means that as long as a human does not affect investment decisions made by the predefined algorithms and only executes orders suggested by the algorithms manually, a fund can be considered quantitative. Nevertheless, as Narang (2013) mentions, most quants (he understands quants not only as quantitative funds, nevertheless all quantitative funds apply quantitative strategies in his understanding) execute their orders algorithmically and quants account for the majority of trades executed algorithmically. They were also the investors and primary innovators of algorithmic trading. Referring to a diagram of a typical structure of a quantitative trading strategy proposed by Narang (2013) presented in Figure 1.4. (previous section of this chapter), he mentions that not all actual quantitative trading strategies have execution model, which is crucial in algorithmic trading. Narang (2013) also mentions that the algorithmic execution of trades is not reserved only for quants, as discretionary traders also use algorithmic execution. In such cases, trading algorithms may help with optimization of order parameters, for instance, when a human manager wants to purchase some discretionarily selected securities.

To sum up, quantitative trading does not have to be algorithmic, as there is consent among the academics that in the quantitative funds/quantitative portfolio management/quantitative trading the orders do not have to be executed automatically by the algorithms. Conclusions from the preceding discussion of this section can be graphically depicted as in Figure 1.5.

[1] https://www.knf.gov.pl/en/MARKET/Fintech/Algorithmic_trading (Access 2020-09-20)

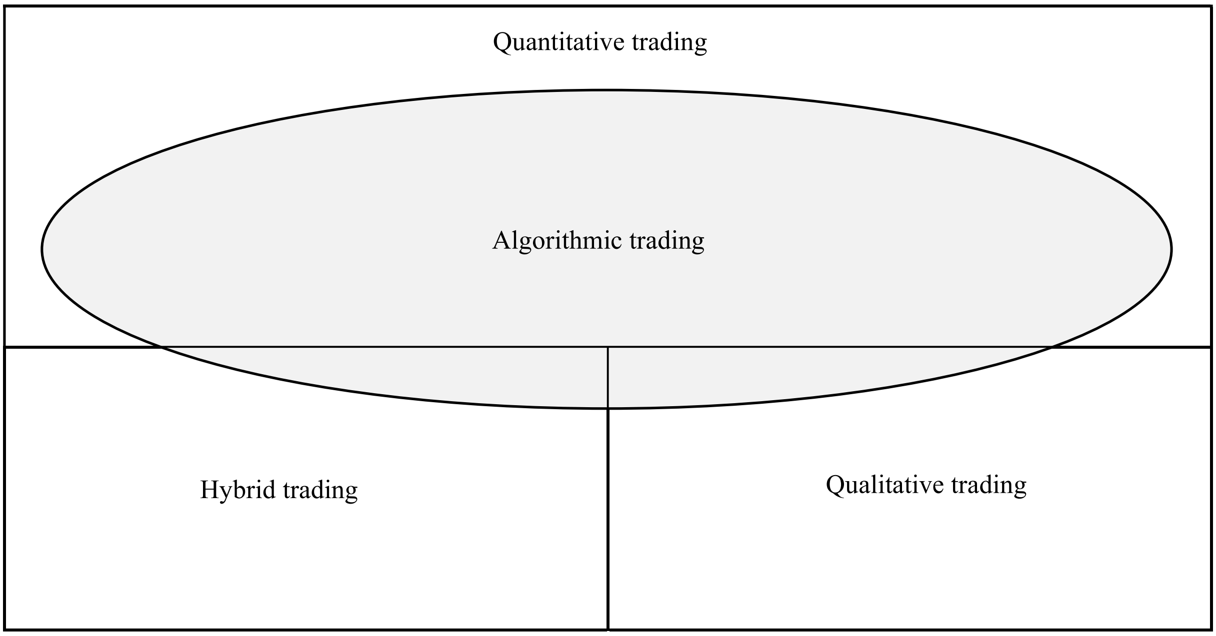

Fig. 1.5. Algorithmic trading in relation to quantitative, hybrid, and qualitative trading. Source: Author's own study

The above-mentioned line of thinking is in line with Gomber, Arndt, Lutat, and Uhle (2013), who propose that quantitative portfolio management does not have to cover trades validation and execution in contrast to algorithmic trading. On the other hand, quantitative portfolio management primarily supports portfolio selection, which is not supported by algorithmic trading. The researchers briefly define quantitative portfolio management as the application of quantitative models to form investment portfolios. According to them, quantitative portfolio management applies algorithms which automate portfolio selection and generation of trading signals. However, a human portfolio manager usually still validates the indications of the algorithms before executing them manually or automatically.

Figure 1.6. illustrates the relation between quantitative portfolio management and algorithmic trading with respect to two dimensions, namely, a degree of latency sensitivity and a degree of automation. Quantitative portfolio management is much less sensitive to latency than algorithmic trading. Unlike algorithmic trading, quantitative portfolio management does not always include trade validation and execution systems, which is illustrated by the dashed line.

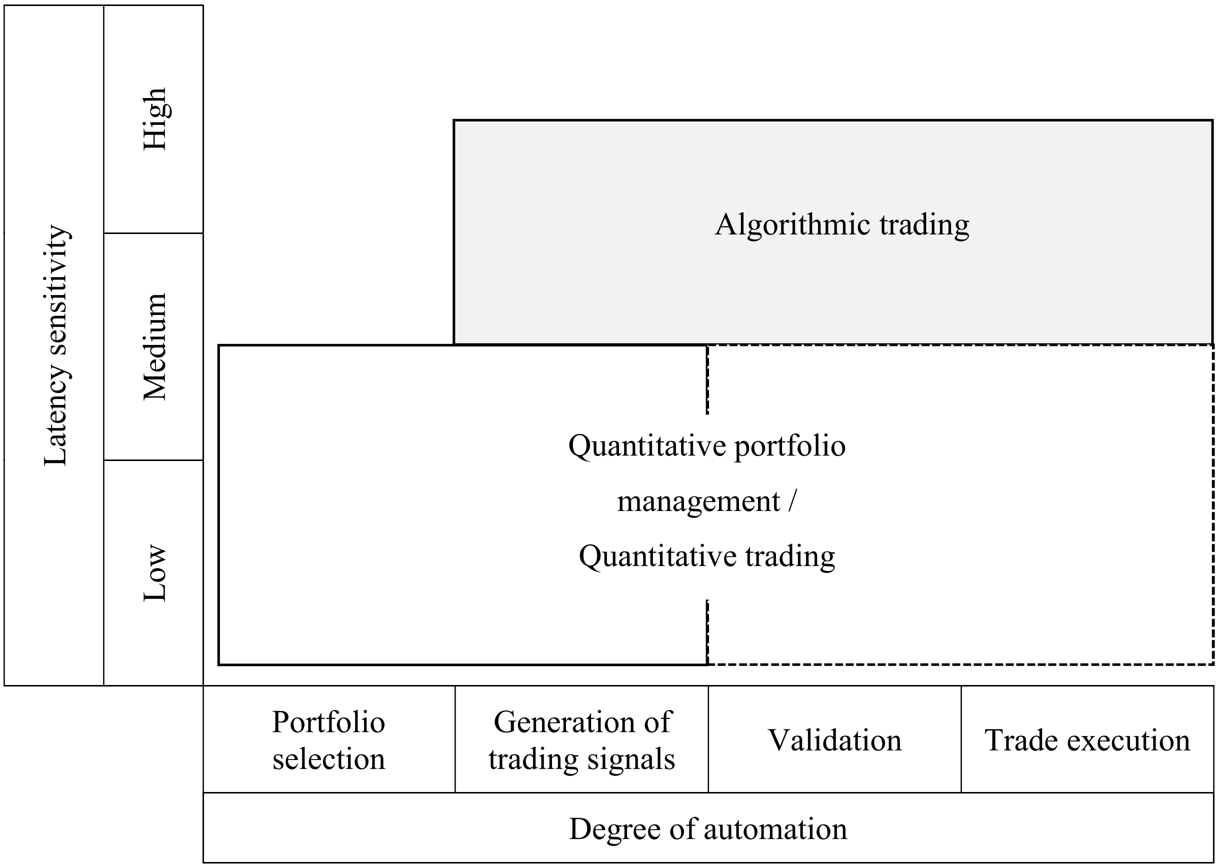

Fig. 1.6. Relation between quantitative portfolio management and algorithmic trading with respect to two dimensions, namely, a degree of latency sensitivity and a degree of automation. Source: Author's own study based on Gomber et al. (2013)

Nevertheless, the above-mentioned line of thinking is inconsistent with some positions of the literature. For example, Chan (2009) and Halls-Moore (2015) consider quantitative trading and algorithmic trading as synonyms. Chan (2009) defines quantitative trading and algorithmic trading very briefly, namely, as trading based strictly on decisions of a computer algorithm. Halls-Moore (2015) defines quantitative, algorithmic, automated, and systematic trading as the use of an automated system that carries out trades, executed without human intervention, by predetermined algorithms.

As a concept of algorithmic trading is delved into, it is worth mentioning another popular term connected with algorithmic trading, i.e., high-frequency trading (commonly referred briefly to as HFT). Due to its importance to financial markets, the same as algorithmic trading, high-frequency trading has been regulated in many legislations and defined by regulators and academics. For instance, Article 3, paragraph 2c of the Polish Financial Instruments Trading Act (2005) defines high-frequency algorithmic trading technique as algorithmic trading which uses IT systems enabling shortening of order sending time to the system of its execution, as well as algorithmic trading which uses IT systems analysing data from financial market causing an immediate usage of a computer algorithm with no human intervention. Furthermore, in the high-frequency algorithmic trading technique, numerous messages are sent to a trading venue (a high message intraday rate). Again, the same as in the case of the algorithmic trading definition, the definition of the high-frequency algorithmic trading technique provided by Article 3, paragraph 2c of the Polish Financial Instruments Trading Act (2005) is in line with the definition provided by Article 4, paragraph 1, point 40 of MiFID II. Article 19 of the Commission Delegated Regulation 2017/565 of 25 April 2016 details the abovementioned definitions clarifying the term of a high message intraday rate. The intraday message rate can be considered high if the average message submission constitutes at least 2 messages per second (in the case of any single financial instrument on a trading venue) or at least 4 messages per second (in the case of all financial instruments on a trading venue) (Karkowska & Karasiński, 2020).

Figure 1.7. supplements the already presented relation of algorithmic trading to quantitative, hybrid, and qualitative trading (Figure 1.5.), with high-frequency trading.

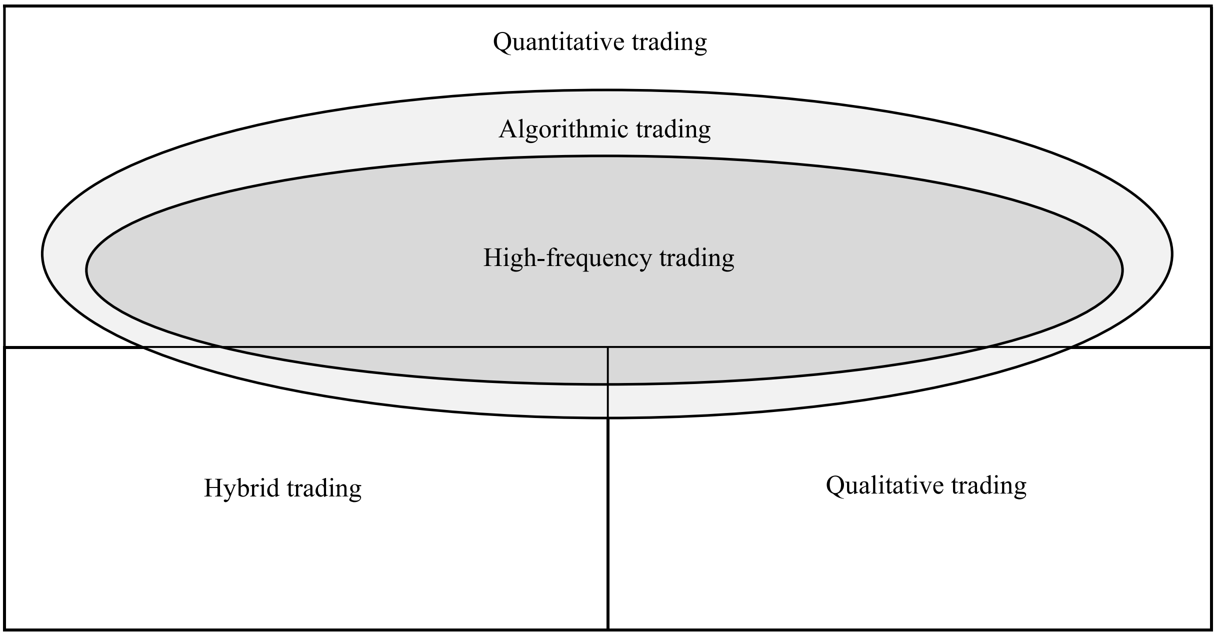

Fig. 1.7. Algorithmic and high-frequency trading in relation to quantitative, hybrid, and qualitative trading. Source: Author's own study

Gomber et al. (2013) analysed various legal and academic definitions of algorithmic and high-frequency trading and proposed that there is no general agreement on a single definition. Their work led to the distinction of some common features of algorithmic and high-frequency trading, features specific for algorithmic trading only, and features specific for high-frequency trading only, which commonly appeared in definitions analysed by the researchers.

Common features of algorithmic and high-frequency trading proposed by Gomber et al. (2013) are presented below, nevertheless the authors stipulate that some features do not have to appear in the actual algorithmic trading and high-frequency system:

- pre-designed trading rules,
- used by professionals,
- real-time market data analysis,
- automated order submission,
- automated order management,

- no human intervention,
- direct access to a trading venue system.

Features specific for algorithmic trading, distinguished by Gomber et al. (2013) on the basis of their review of the issue-related literature:

- agent trading (securities of customers are held over longer time periods),
- minimizing market impact for larger orders,
- benchmark-following,
- longer holding periods, e.g., days, weeks, months.

Features specific for high-frequency trading, distinguished by Gomber et al. (2013) on the basis of their review of the issue-related literature:

- numerous orders,
- orders cancelled rapidly,
- proprietary trading (traders mostly manage their own capital only),
- as the middleman makes profit from purchase and sale,
- at the end of the day there is no significant position (no over-night positions),
- very short holding periods,
- focus on instruments which are highly liquid,
- low margins per trade,
- requires low latency connections to trading venues,
- utilizing co-location services (placing hardware of traders close to the trading venue's servers) and individual data feeds.

Figure 1.8. supplements Figure 1.6. with high-frequency trading, a highly sensitive to latencies subgroup of algorithmic trading.

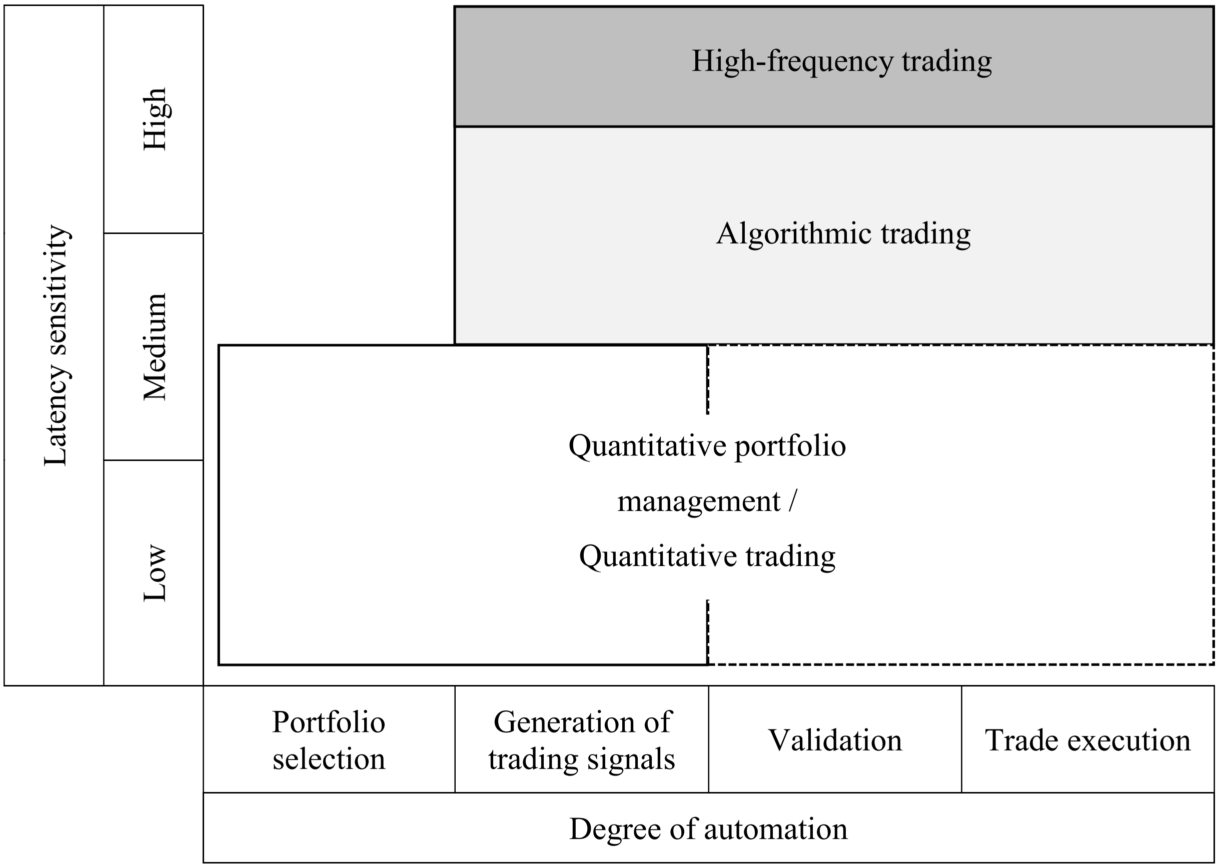

Fig. 1.8. Relation between quantitative portfolio management, algorithmic trading, and high-frequency trading with respect to two dimensions, namely, a degree of latency sensitivity and a degree of automation. Source: Author's own study based on Gomber et al. (2013)

1.4. The criticism of quantitative funds

Many studies dedicated to quantitative funds raise an issue of their not necessarily good reputation in the eyes of investors. For instance, according to Harvey et al. (2017) some allocators unwillingly allocate to systematic funds (as they call them) or even avoid it partially or entirely, due to myths about systematic funds, circulating in the hedge fund industry. AQR (2017) enumerates and denies several misconceptions that arose with systematic funds (as they call them). Lakonishok and Swaminathan (2010), Lin (2019), Thurston (2011), Harvey et al. (2017) and AQR (2017) discuss criticism towards performance of systematic funds. Fabozzi et al. (2008) following a very popular paper of Khandani and Lo (2011) i.e., 'What happened to the quants in August 2007? Evidence from factors and transactions data', aim to find out why quantitative funds created their own herd behaviour during the global financial crisis in the second half of 2007, even though they were designed to avoid herd behaviour of qualitative funds.

Harvey et al. (2017) propose the following reasons for the lack of confidence in systematic funds, which can be often met in the industry:

- homogeneity,
- difficulties in understanding,

- worse performance compared to discretionary funds,
- less transparent compared to discretionary funds,
- doomed to perform worse than discretionary funds due to reliance only on historical data.

According to Harvey et al. (2017), who want to prove that the lack of confidence in systematic funds has no reasonable grounds, the abovementioned reasons seem to be in line with a distrust of the system or the so-called ‘algorithm aversion’, a phenomenon presented, for instance by Dietvost, Simmons, and Massey (2015). According to Harvey et al. (2017) the lack of confidence in systematic funds is confirmed by the share of systematic funds in the hedge fund industry (hedge funds included in the HFR database). At the end of 2014 only 31% of hedge funds were systematic and systematic funds managed only 26% of total assets under management. Of course, there can be other reasons for such a dominance of discretionary funds which are not related to the unjustified lack of confidence in systematic funds suggested by Harvey et al. (2017). The systematic approach is not the only right approach to portfolio management, and it is not better than the discretionary approach in all respects. It is basically different with its drawbacks and benefits. Some discretionary funds still did not manage to incorporate quantitative techniques yet or it was their decision not to change the approach to portfolio management.

Misconceptions about systematic portfolio management and arguments against these misconceptions proposed by AQR (2017) are presented in Table 1.8.

Misconceptions about systematic portfolio management	**Arguments against misconceptions about systematic management**
Hard to understand ‘black boxes’	Inputs, outputs, and process can be complex, nevertheless, they still can be understood
No use of fundamental inputs	Fundamental inputs are used by most systematic managers
Overreliance on numbers and lack of human judgement	Human overlay can be met at the stage of the design, revision, implementation and supervision
High dependence on historical data	Historical data are used by both approaches to portfolio management. Overfitting to historical data can be avoided in a well-designed systematic investment process
Too high diversification	Concentration is commonly identified with discretionary portfolio management. It can easily increase risk, but its impact on returns is hard to predict. Repeatable systematic processes allow for better diversification along many dimensions and across well-rewarded factors. It also helps improve risk-adjusted returns due to diversifying away idiosyncratic risk
Lack of information on individual companies	Due to advances in technology, systematic managers can include more and more information on individual companies in the process they rely on

Crowding and high correlation concerns	Correlation among discretionary funds is not less than correlation among systematic funds

Tab. 1.8. Misconceptions about systematic portfolio management and arguments against these misconceptions proposed by AQR (2017). Source: Author's own study based on AQR (2017)

Moving on to the studies addressing criticism on performance, crowding, homogeneity and high correlations among quantitative funds, Lakonishok and Swaminathan (2010) in the study on long active money managers included in the eVestment Alliance database, covering the period of 2001-2009, found that quantitative and fundamental managers had low and similar average pairwise correlations of monthly benchmark-excess returns. The dispersion of alphas in both groups was also similar. Additionally, no substantial differences in performance were observed between quantitative and fundamental funds.

Thurston (2011) conducted a study on equity funds available in the Russel database, covering years 2003-2009. In addition to the split of funds into quantitative and traditional (as he called them), the researcher divided the funds into different geographies. The study aimed to find out if there is any support for criticism of the underperformance of quantitative funds during the global financial crisis in the period 2007-2009. Despite the criticism on high correlations between the quant funds, Thurston (2011) proposed that the pairwise 3-year rolling correlations of the excess returns between quant funds were low and a little higher than correlations among the traditional funds. The correlations between quant and traditional funds were also low. The researcher found that key factors such as value, capitalization, and momentum contributed to the crowding responsible for the underperformance of the quant funds in the crisis period. The performance patterns were similar across the geographies, and the performance of the quant funds was cyclical.

Lin (2019) in the study on long-only Australian and Global equity funds coming from the eVestment and Morningstar databases, covering the period from January 2007 to June 2019, found low pairwise correlations among quantitative funds. Similarly, low pairwise correlations were observed in the groups of fundamental and quantamental funds. The researcher proposed that on average, fundamental funds generated higher returns but also higher risk compared to quantitative funds. However, on the basis of behaviour of excess returns over time, Lin (2019) suggests that excess returns tended to be time-period dependent and none of the styles had a clear advantage.

In the study on equity funds retrieved from the eVestment database, covering a 10-year period ending on 31 March 2017, AQR (2017) found that both systematic and discretionary approaches yielded similar excess returns. However, the tracking error of the systematic strategies was lower and their information ratio was slightly higher compared to discretionary funds. Thus, the authors propose that systematic funds generated slightly higher risk-adjusted returns. As far as correlations between excess returns generated by managers are concerned, according to AQR (2017), correlations in the group of systematic funds were low, the same as in the case of discretionary funds. In addition, the correlations between systematic and discretionary funds also turned out to be low.

In the study on macro and equity hedge funds coming from the Hedge Fund Research Database, using data from 1996-2014, Harvey et al. (2017) proposed that systematic equity managers delivered lower raw returns than discretionary equity managers. However, after adjusting for volatility and factor exposures, systematic equity managers outperformed discretionary managers. When it comes to a sample of macro managers, systematic funds generated higher raw returns and risk-adjusted returns compared to discretionary funds. Furthermore, the results of the study by Harvey et al. (2017) suggested that the levels of performance spread were similar for systematic and discretionary managers. Regarding factor attribution, in both macro- and equity strategies, more of the returns can be attributed to factor exposures in the case of discretionary funds.

Most of the aforementioned criticism seems to result from a poor performance of quantitative funds in the second half of 2007, which was especially emphasized in a very willingly cited article by Khandani and Lo (2011), i.e., 'What happened to the quants in August 2007? Evidence from factors and transactions data'. After a successful 2000-2005 period for quantitative funds, when (according to some sources) quantitative funds grew at twice the rate of all other funds, due to good performance, quantitative funds faced the issue of underperformance related to the global financial crisis (Fabozzi, Foracrdi, & Jonas, 2008). Khandani and Lo (2011) simulated some strategies applied to US stocks, popular among high-frequency market makers, which could be classified as short-term market-neutral mean-reversion strategies, in order to look closely at the 'Quant Meltdown' of August 2007. The results of the study suggest that the 'Quant Meltdown' was the result of a crowded application of similar strategies, unwinding positions, and lack of liquidity. According to a survey conducted by Fabozzi, Foracrdi and Jonas (2008), among asset managers, investment consultants, consultants to the industry and rating agencies, the positions unwinding was a major factor, which contributed to the losses incurred by some quantitative equity funds in the early stages of the financial crisis. The next significant factor contributing to the 'Quant Meltdown' of August 2007 indicated by the survey participants was the investment management process of the quants itself. Other factors leading to the herd behaviour of quant funds were: high global ratio of short to long positions, overreaction of risk models, undetermined risk factors, and misaligned behaviour of equity derivatives.

1.5. Conclusions

The review of the definitions of quantitative and qualitative funds conducted in this chapter indicates that there is no complete consensus among researchers on the question of formulating definitions of discussed investment funds. Moreover, there is no complete consensus pertaining to nomenclature. Due to this, the need to formulate universal definitions was born. Taking into account that the answer to the question 'is the investment process predefined and automated?' is the most important criterion that separates one group from the another, quantitative funds were defined as investment funds in which investment decisions are based on the indications of a predefined and automated investment process with none or a limited human intervention. On the other hand, qualitative funds were defined as funds in which investment decisions are made using the judgement of a human manager, based on his skills and intuition. In addition, some managers also mix quantitative and qualitative approaches to portfolio management in many different ways. A hybrid fund was defined as an investment fund in which investment decisions are based on the cooperation of a predefined automated investment process and the judgment of the human manager. The review of the literature made in this chapter shows many clear differences between quantitative and qualitative investment funds, highlighting the need of the allocators for information on the affiliation of funds to one of these groups.

Moreover, this chapter raised an issue of the criticism of quantitative funds, and misconceptions arose about them, which were discussed and mostly challenged in the issue-related studies. Additionally, the material presented in this chapter introduced a typical structure of a quantitative trading strategy proposed by Narang (2013) and Guo et al. (2017). Finally, this chapter discussed some other terms that are related to quantitative funds, like algorithmic and high-frequency trading.

The review of definitions conducted in this chapter allowed to become familiar with the substance of quantitative and qualitative funds. It is essential from the point of view of the empirical study that requires to select those groups of funds from a whole sample of investment funds retrieved from the applied database. The split of funds will be crucial in terms of the verification of the research hypotheses, as well as in terms of answering some supplementary research questions posed in the introduction.

2. The importance of quantitative funds to financial markets

Based on widely accessible industry reports, this chapter makes an attempt to investigate the meaning of quantitative funds to financial markets. The utilized industry reports were prepared by the market research firms such as Hedge Fund Research, Morningstar (Morgan Stanley Research), TABB Group or Aite Group (Goldman Sachs Global Investment Research). The reports were published mostly by Financial Times, The Economist, and The Wall Street Journal.

Due to high costs related to the purchase of full market reports, and the necessity to use some widely accessible estimates, presented in the financial press only, the choice of relevant market data was significantly limited. However, despite the limited choice of accessible estimates, mostly referring to assets under management, net asset flows, and participation in trading volume on different financial markets, the utilized issue-relevant market data allowed for drawing some interesting conclusions pertaining to the importance of quantitative funds to financial markets. In addition, the collected data also allowed to draw some interesting conclusions related to the importance of other related phenomena, such as quantitative trading and algorithmic trading, including high-frequency trading.

The collected estimates deliver many interesting information, for example, pertaining to assets under management and net asset flows of hedge and mutual funds that apply quant and non-quant strategies. Furthermore, the estimates refer to the contribution of the aforementioned investment funds, quantitative trading, and algorithmic trading (including high-frequency trading) to the trading volume generated on different markets. Such information allow for answering a question of whether quantitative funds, quantitative trading, and algorithmic trading (including high-frequency trading), have any significant meaning to financial markets. Moreover, this chapter discusses some selected studies on the impact of algorithmic trading (in which quantitative trading also has its share) on financial markets.

2.1. The position of quant funds in the hedge fund and mutual fund industry

The literature raising the issue of quant funds indicates that quant funds especially prefer to run their operations as hedge funds (e.g., Fabozzi, Foracrdi, & Jonas, 2008; Khandani, & Lo, 2011). For this reason, they have fewer transparency and regulatory requirements, as well as more freedom in implementing more aggressive trading strategies than mutual funds (Cartea, Jaimungal, & Penalva, 2015). Among the studies on the performance of quant funds, the majority of them clearly declare to analyse the universe of hedge funds (Aldridge, 2019; Chincarini, 2014; Chuang & Kuan, 2018; Harvey et al., 2017; Khandani & Lo, 2011), and just few of them analyse mutual funds (Abis, 2018; Parvez & Sudhir, 2005). It is also much easier to find some widely accessible, overall market estimates referring to quant funds in the hedge funds universe. Such data, particularly, come from the Hedge Fund Research database and the market reports, willingly exploited in academic studies and financial press.

Figure 2.1. presents the assets under management of quant hedge funds, non-quant hedge funds and a whole global hedge fund industry according to data provided by the Hedge Fund Research (including split between the quant and non-quant hedge funds), which was presented by Wigglesworth (2017), Walker (2019), Williamson (2018), and Hedge Fund Research (2019).

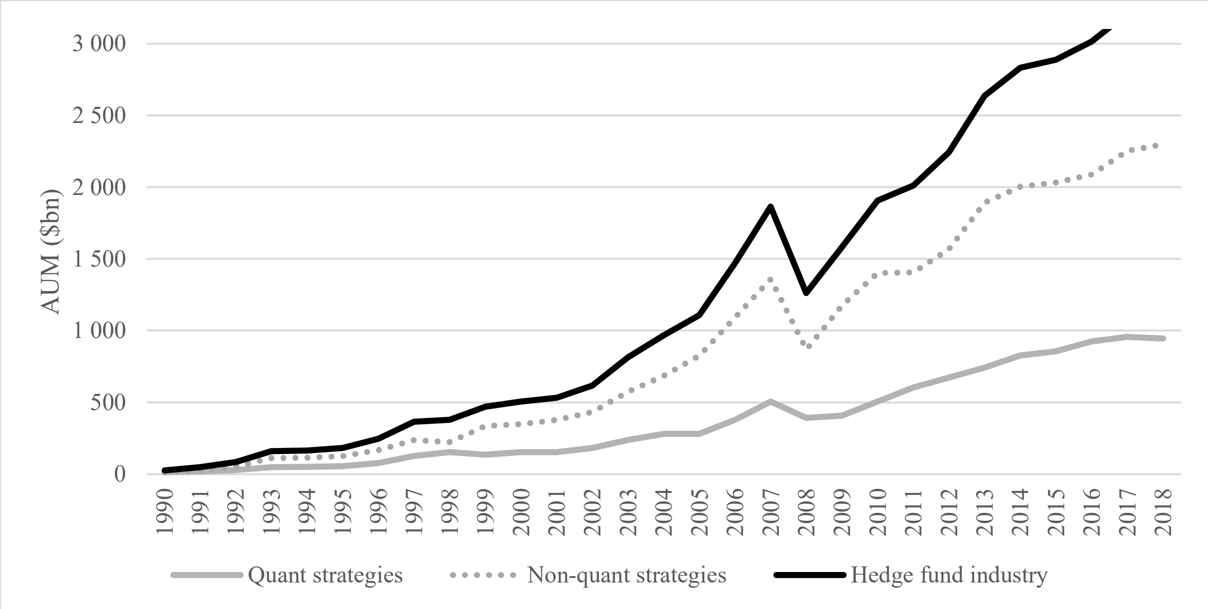

Fig. 2.1. The assets under management of quant hedge funds, non-quant hedge funds, and a whole global hedge fund industry, according to Hedge Fund Research. Source: Author's own study based on Wigglesworth (2017), Walker (2019), Williamson (2018), and HFR (2019).

The regular growth of a whole hedge fund industry in years 1990-2007, of about 28.00% CAGR (compound annual growth rate), was stopped by the 2008 global financial crisis. CAGR of the quant and non-quant hedge funds, in the period 1990-2007, amounted to about 23.47% and 30.88%, respectively. A huge drop of assets under management of a whole global hedge fund industry, quant and non-quant hedge funds, in years 2007-2008, caused by the 2008 global financial crisis, amounted to about -32.33% (hedge fund industry), -22.22% (quant hedge funds), and -36.08% (non-quant hedge funds), respectively. Starting from 2008, the assets under management of hedge fund industry (including quant and non-quant strategies), were in the upward trend with a CAGR of around 9.91%. The same as in the precrisis period, the assets under management of non-quant hedge funds rose faster compared to quant funds, with CAGR of around 10.21%. The CAGR of non-quant hedge funds was about 9.20%. The assets under management of quant hedge funds rose slower. Nevertheless, they were less fragile to the 2008 global financial crisis.

Since 2016, the assets under management of the hedge fund industry have fluctuated around $3 trillion. Due to the impact of the coronavirus pandemic on global financial markets, the assets under management of hedge fund industry, fell 11% in the first quarter of 2020 to $2.96 trillion, from $3.33 trillion at the end of 2019. The assets under management of hedge fund industry recovered by 7.4% in the second quarter of 2020 and amounted to $3.18 trillion as at June 30th, 2020 (Williamson, 2020).

Figure 2.2. presents the share of quant hedge funds and non-quant hedge funds in the assets under management of a whole global hedge fund industry. Figure 2.2. has been prepared on the basis of data presented in Figure 2.1., i.e., on the basis of data provided by Hedge Fund Research (including split between quant and non-quant hedge funds), which have been presented by Wigglesworth (2017), Walker (2019), Williamson (2018), and HFR (2019). The share of quant funds in the assets under management of the global hedge fund industry did not seem to change much over the years, especially in the period 1999-2018, when their share oscillated around 29%. Despite the growing popularity of quantitative portfolio management techniques, mentioned, for instance, by Chincarini (2014), and rapidly evolving factors like technology development that stimulates the development of quantitative portfolio management techniques, a relatively constant share of quant funds in the assets under management of the global hedge fund industry, oscillating around 29%, suggests that quant funds probably are not going to increase their share or dominate the industry in the upcoming years. Nevertheless, without an in-depth study, a future trend of the share of quant funds in the assets managed by the hedge fund industry is difficult to predict. Participants of the survey by Fabozzi, Foracrdi, and Jonas (2008), who faced a similar question as to whether the quantitatively managed funds would not increase their market share relative to traditionally managed funds, due to a weak performance in 2007, were not unanimous. 39% of the survey participants agreed, 42% disagreed, and 19% shared no opinion.

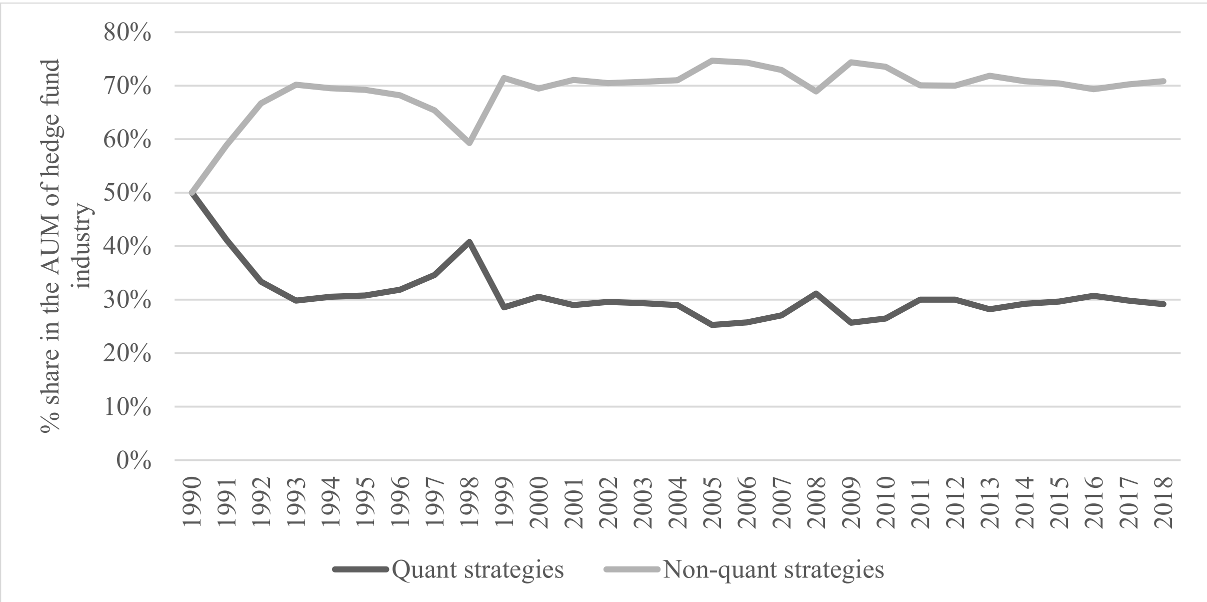

Fig. 2.2. The share of quant hedge funds and non-quant hedge funds in assets under management of a whole global hedge fund industry, according to Hedge Fund Research. Source: Author's own study based on Wigglesworth (2017), Walker (2019), Williamson (2018), and HFR (2019).

As Figure 2.2. refers only to the share of quant hedge funds and non-quant hedge funds in the assets under management of a whole global hedge fund industry, there are more estimates needed to be able to fully confirm the stagnation of the share of quant hedge funds in the hedge funds industry. Such estimates would be the number of quant and non-quant hedge funds. However, they were not widely accessible.

Without an in-depth study the reasons for a stagnating share of quant hedge funds in the assets managed by a global hedge fund industry can only be guessed. For instance, the expansion of the hedge fund industry by quant funds could have been held due to misconceptions that arose on quantitative portfolio management in the industry, as mentioned by Lakonishok and Swaminathan (2010), Lin (2019), Thurston (2011), Harvey et al. (2017), and AQR (2017). Such misconceptions could have held a common implementation of quantitative portfolio management techniques. This hypothesis was shared by most respondents of the above-mentioned survey by Fabozzi, Foracrdi, and Jonas (2008), who were asked if the quantitative equity portfolio management would continue to be dominated by many small quant boutiques and just a few large players. 77% of the survey participants agreed, 10% disagreed, and 13% shared no opinion.

Figure 2.3. presents net assets flows into the quant hedge funds, non-quant hedge funds and a whole global hedge fund industry, according to Hedge Fund Research (including split between the quant and non-quant hedge funds), which have been presented by Walker (2019), Fletcher (2020), and Stanford (2016).

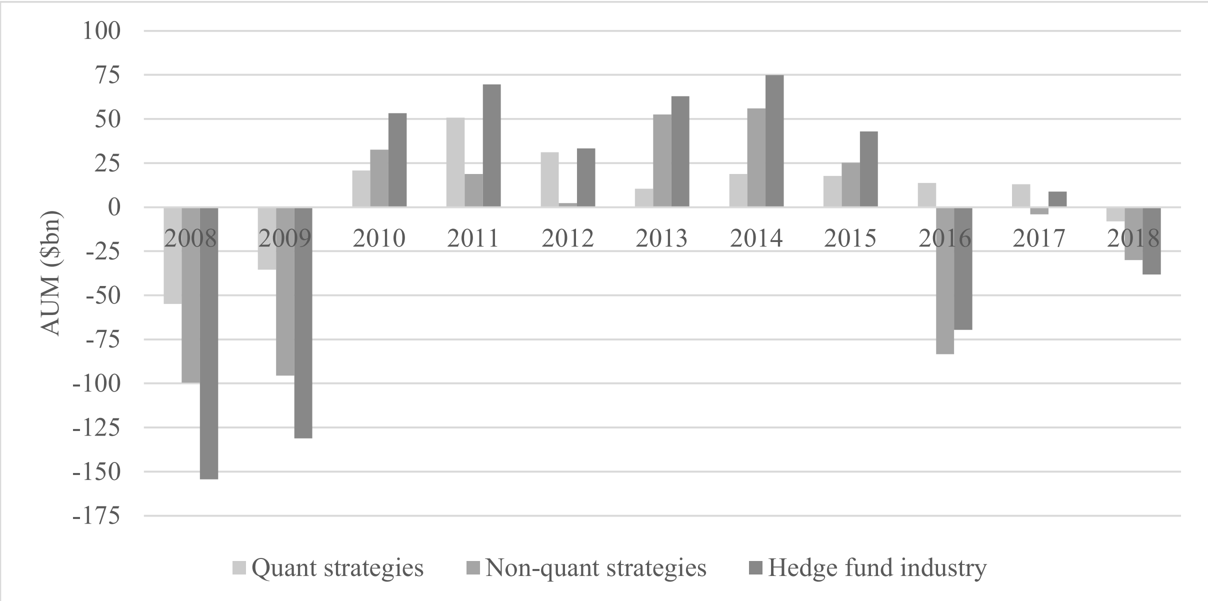

Fig. 2.3. The net assets flows into quant hedge funds, non-quant hedge funds, and a whole global hedge fund industry, according to Hedge Fund Research. Source: Author's own study based on Walker (2019), Fletcher (2020) and Stanford (2016).

The 2008 global financial crisis significantly contributed to the outflows of assets from a whole hedge fund industry, including both quant and non-quant hedge funds. As the inflows of assets to the hedge fund industry reached nearly $195 billion in 2007, in 2008 the outflows reached nearly $155 billion. Asset inflows of still have not returned to the level before the 2008 global financial crisis (Stanford, 2016).

Outflows from the entire hedge fund industry were also reported in 2016, 2018, 2019, and 2020. In 2019, the entire hedge fund industry suffered assets outflows that reached nearly

$43 billion (Fletcher, 2020). According to Funds Europe, a financial website that utilizes data provided by Hedge Fund Research, the hedge fund industry suffered net assets outflows in 2020 again. In the first quarter of 2020, net assets outflows from the hedge fund industry amounted to $34.86 billion, while in the second quarter of 2020, they amounted to $12.2 billion.

Whereas the share of quant hedge funds in the assets under management of the global hedge fund industry remains rather stable, oscillating around 29% (see Figure 2.2.), the share of quant hedge funds in the net assets flows of global hedge fund industry changes significantly over the years, as presented in Figure 2.4. Figure 2.4. should be analysed in connection with Figure 2.3. as directions of net assets flows may be different (inflows vs. outflows) for quant hedge funds, non-quant hedge funds, and the entire hedge fund industry.

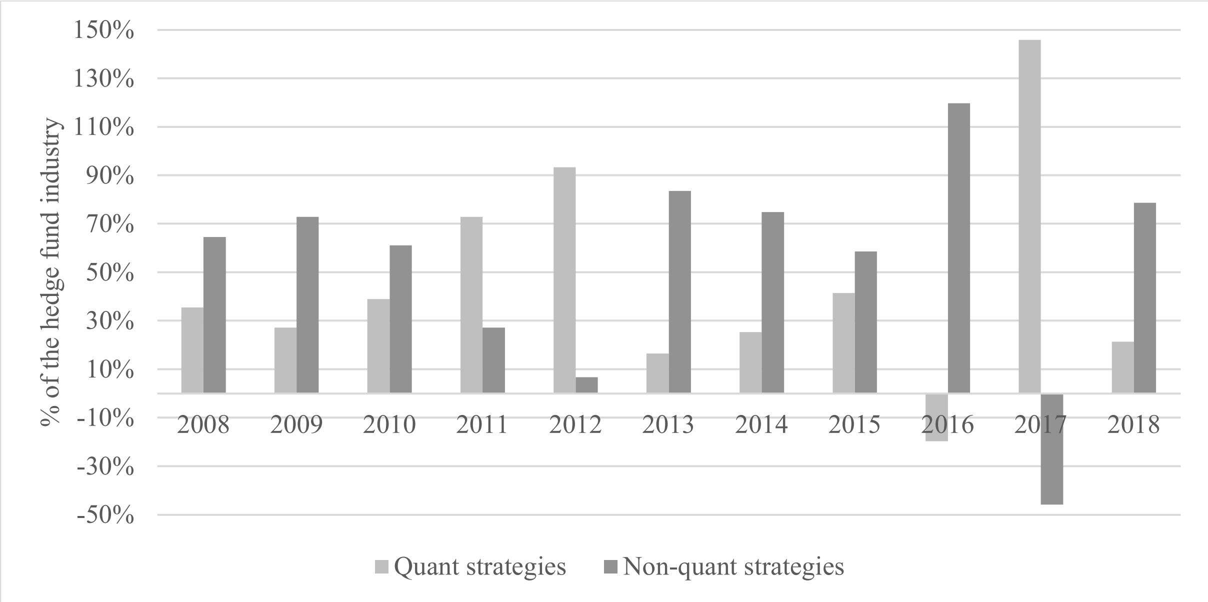

Fig. 2.4. The share of quant hedge funds and non-quant hedge funds in the net assets flows of the global hedge fund industry, according to Hedge Fund Research. Source: Author's own study based on Walker (2019), Fletcher (2020) and (Stanford, 2016).

Although quant hedge funds make up about 29% of the hedge fund industry (taking assets under management into account), in 2011 and 2012 their net assets inflows exceeded inflows to non-quant hedge funds and even compensated the outflows from the non-quant hedge funds in 2016 and 2017. However, in other periods, the net assets inflows to quant hedge funds seem to be lower than inflows to non-quant hedge funds. Nevertheless, also the outflows from quant hedge funds seem to be lower than outflows from non-quant hedge funds. The same as in the case of the analysis of assets under management, the analysis of net assets flows suggests that quant hedge funds are less fragile to market turmoil compared to non-quant hedge funds. Sometimes, quant hedge funds seem to be even immune to market turmoil and gain net assets inflows when a whole hedge fund industry suffers net assets outflows (see year 2016 in Figure 2.3.) or when net assets inflows into hedge fund industry are smaller and non-quant hedge funds suffer outflows (see year 2017 in Figure 2.3.).

Moving onto the quant mutual funds, Figure 2.5. shows the assets under management of US-domiciled quant mutual funds and their share in the assets under management of US-domiciled mutual fund industry, as at July 31st, 2017, according to Morningstar, Morgan Stanley Research, as presented by Wigglesworth (2018) and Butcher (2017). The growth of assets under management of US-domiciled quant mutual funds, in the period 2010-2017, was quite regular, of 17.96% CAGR. The regularity of growth also pertained to the share of quant mutual funds in the assets under management of US-domiciled mutual fund industry. Unlike quant hedge funds, whose share in the AUM of the global hedge fund industry stagnates over time (see Figure 2.2.), the US-domiciled quant mutual funds systematically gain share in assets managed by US-domiciled mutual fund industry. However, their share in total assets managed by US-domiciled mutual funds is much smaller.

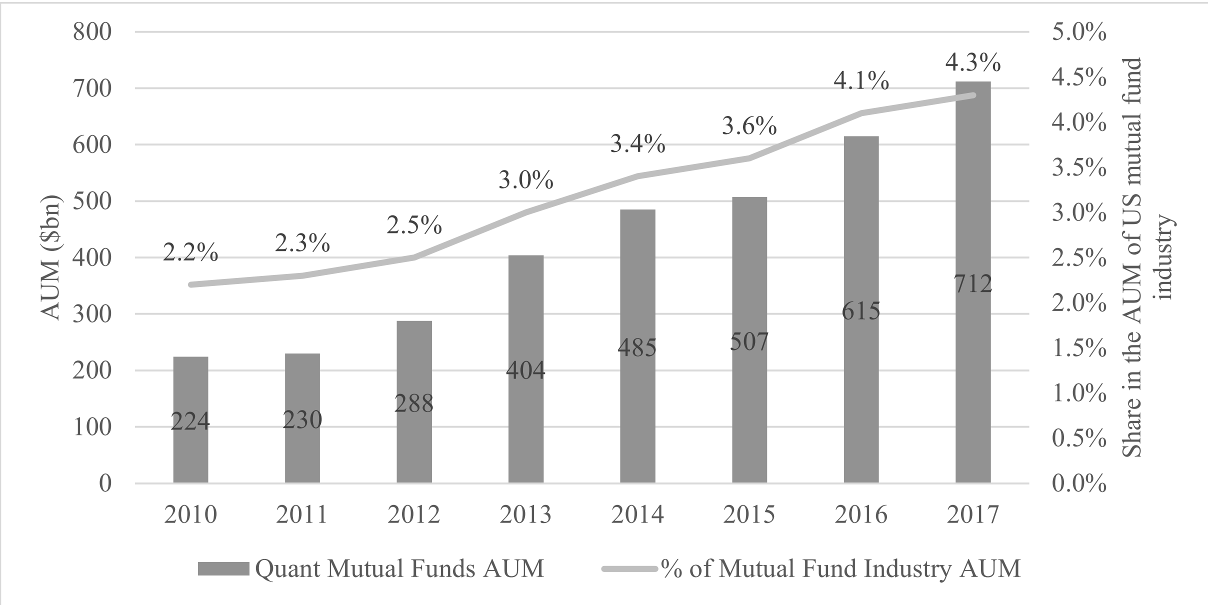

Fig. 2.5. Assets under management of US-domiciled quant mutual funds and their share in the assets under management of US-domiciled mutual fund industry, as at July 31st, 2017, according to Morningstar, Morgan Stanley Research. Source: Author's own study based on Wigglesworth (2018) and Butcher (2017).

The data pertaining to the assets under management of US-domiciled quant mutual funds presented in Figure 2.5. are also presented in Figure 2.6., but this time in comparison with US-domiciled smart beta ETFs, quant hedge funds and their joint assets (total) as at July 31st, 2017, according to Morningstar, Morgan Stanley Research, as presented by Wigglesworth (2018). In the period 2010-2017, growth of each fund category was stable and regular, of 23.51% (smart beta ETFs), 17.96% (quant mutual funds), 10.62% (quant hedge funds), 16.30% (all categories) CAGR. In 2011 and 2012, the assets of quant hedge funds exceeded the assets of quant mutual funds. However, in the following years, the assets of quant mutual funds were larger, and their advantage over quant hedge funds rose systematically. It is worth mentioning that smart beta ETFs systematically decreased the advantage of quant hedge funds, nevertheless, in the entire period presented in Figure 2.6., the assets managed by smart beta ETFs were smaller than the assets managed by quant hedge funds.

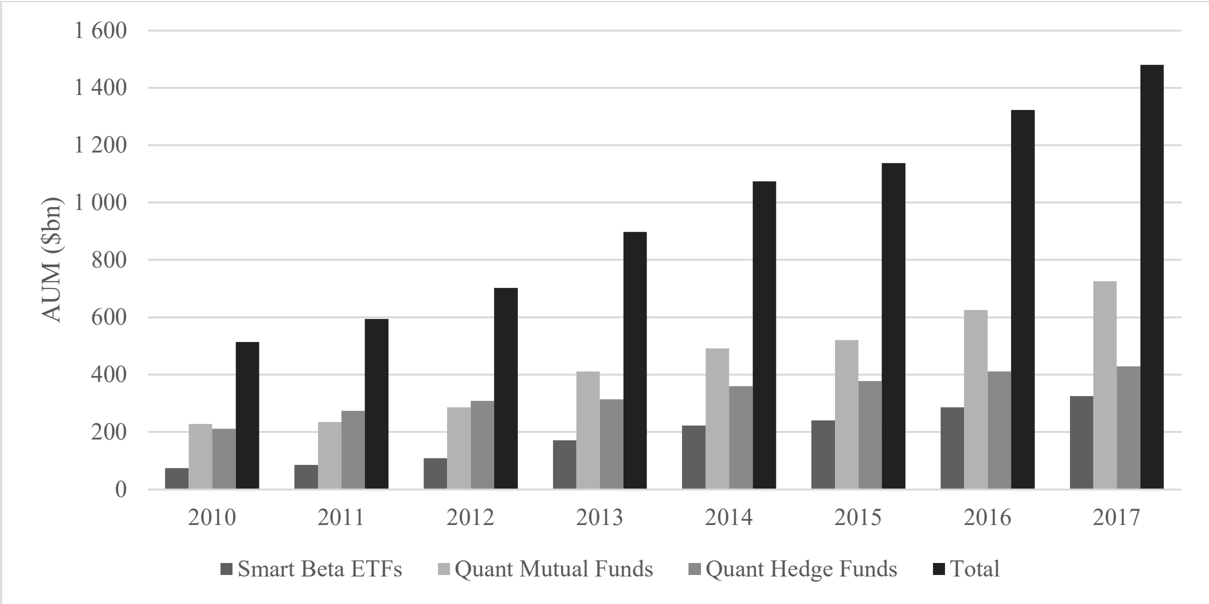

Fig. 2.6. Assets under management of US-domiciled smart beta ETFs, quant mutual funds, quant hedge funds, and their joint (total) assets as at July 31st, 2017, according to Morningstar, Morgan Stanley Research. Source: Author's own study based on Wigglesworth (2018).

Due to some limitations in collecting market data that pertain to assets under management of quant hedge funds (see Figures 2.1.-2.2.), estimates referring to quant hedge funds pertain to a global industry only, with no geographic split. On the other hand, data referring to quant mutual funds pertain to the US-domiciled industry only (see Figures 2.5.-2.6.), what makes the comparison between quant hedge and quant mutual funds very limited and difficult. Nevertheless, the estimates of Morningstar, Morgan Stanley Research, utilized by Wigglesworth (2018) and presented in Figure 2.6., allow for a brief comparison of assets managed by the US-domiciled quant hedge and mutual funds. Unfortunately, the author of this study was not able to collect data referring to assets managed by a whole US-domiciled hedge fund industry, what would enable him to expand the comparison to the share of quant funds in each fund class (hedge vs. mutual).

Nevertheless, even with some limitations in access to market data, it was manageable to draw some interesting conclusions when comparing market data pertaining to assets managed by quant hedge funds (see Figures 2.1.- 2.2.) and quant mutual funds (see Figures 2.5.-2.6.). When comparing data presented in Figures 2.1. and 2.6., US-domiciled quant hedge funds constitute a significant part of assets managed by global quant hedge fund industry, oscillating between 42% and 46%, with an average level of 44% in years 2010-2017. Assets managed by both groups have a similar CAGR of 10.62% in the case of US-domiciled quant hedge funds and 9.57% in the case of a global quant hedge fund industry. Due to a significant share of US-domiciled quant hedge funds in the AUM of global quant hedge fund industry and a similar growth rate, it can be supposed that the US-domiciled quant hedge fund industry is responsible for shaping trends of global quant hedge fund industry. The comparison of assets under management of the quant hedge fund groups mentioned above is presented in Figure 2.7.

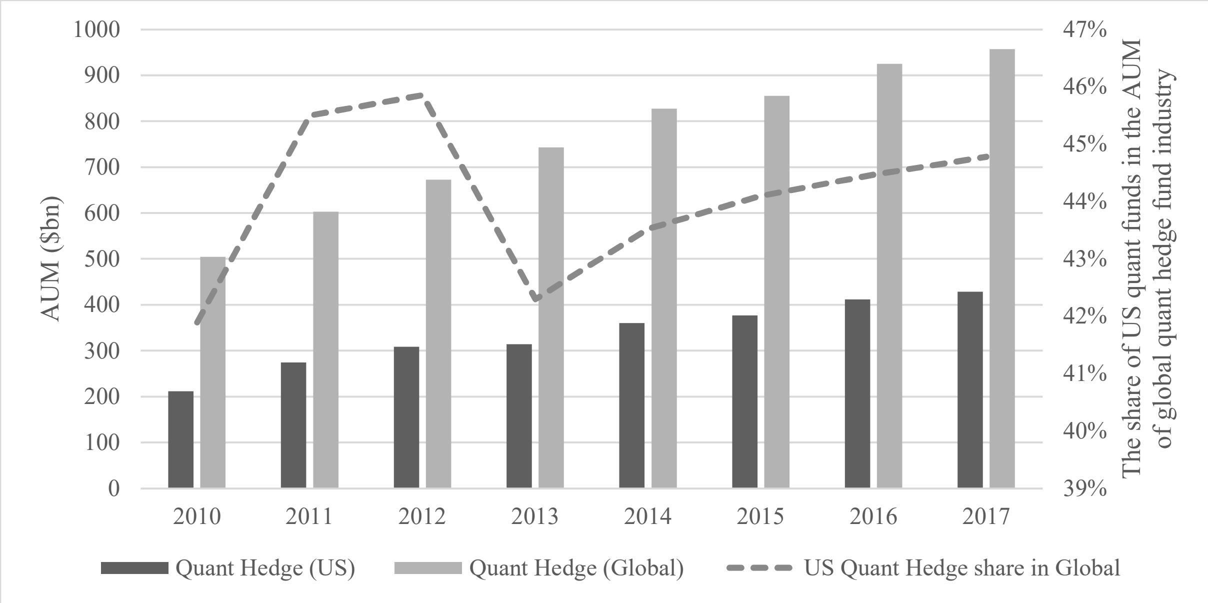

Fig. 2.7. Assets managed by US-domiciled quant hedge funds and the global quant hedge fund industry, as well as the share of US-domiciled quant hedge funds in the assets under management of the global quant hedge fund industry. Source: Author's own study based on the data presented in Figures 2.1. and 2.6.

Market data referring to a number of funds could not be collected. Nevertheless, conclusions coming from the foregoing comparison of AUM across different groups of investment funds seem to contradict with the thesis mentioned earlier in this chapter, stating that quant funds especially prefer to run their operations as hedge funds (e.g., Fabozzi, Foracrdi, & Jonas, 2008; Khandani, & Lo, 2011), The actual number of quant hedge and mutual funds is unknown. Nevertheless, more assets are allocated to quant mutual funds.

Based on data from Morningstar, Morgan Stanley Research, Wigglesworth (2019) provided the structure of assets managed by US-domiciled quant hedge funds as at January 31st, 2019. The breakdown of AUM by the applied strategy (trend-following, statistical arbitrage, equity market-neutral, other) is presented in Figure 2.8.

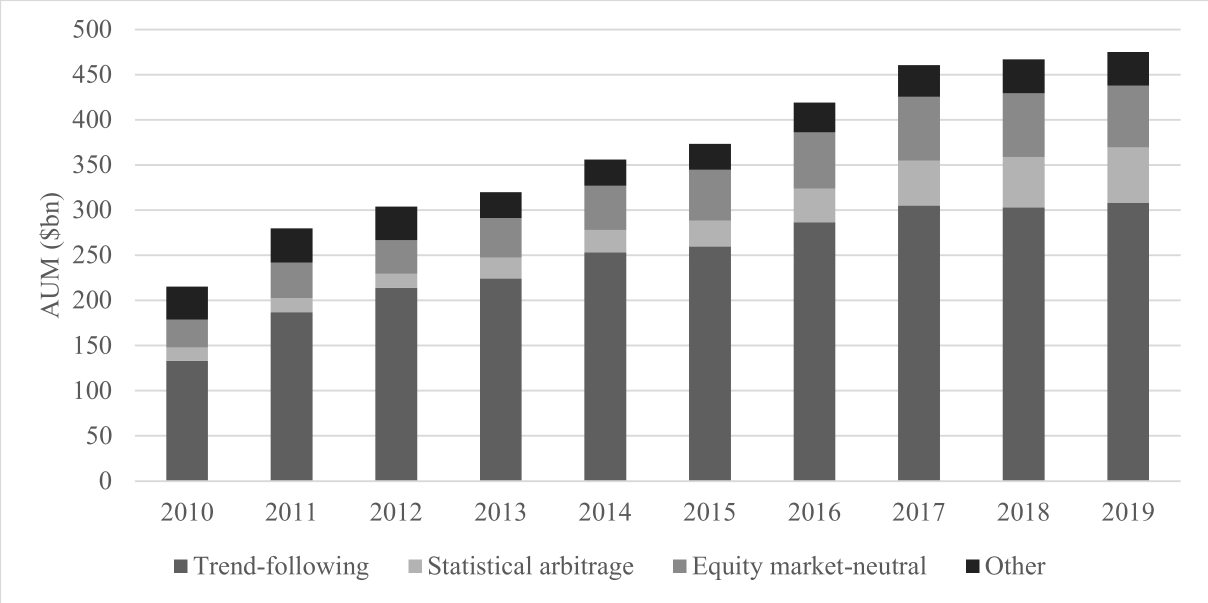

Fig. 2.8. The structure of assets managed by US-domiciled quant hedge funds as at January 31st, 2019, according to Morningstar, Morgan Stanley Research, taking into account strategies applied by quant hedge funds (trend-following, statistical arbitrage, equity market-neutral, other). Source: Author's own study based on Wigglesworth (2019).

The structure of assets managed by US-domiciled quant hedge funds from Figure 2.8. is also presented in the percentage dimension (as a percentage of total assets managed by a whole US-domiciled quant hedge fund industry), in Figure 2.9.

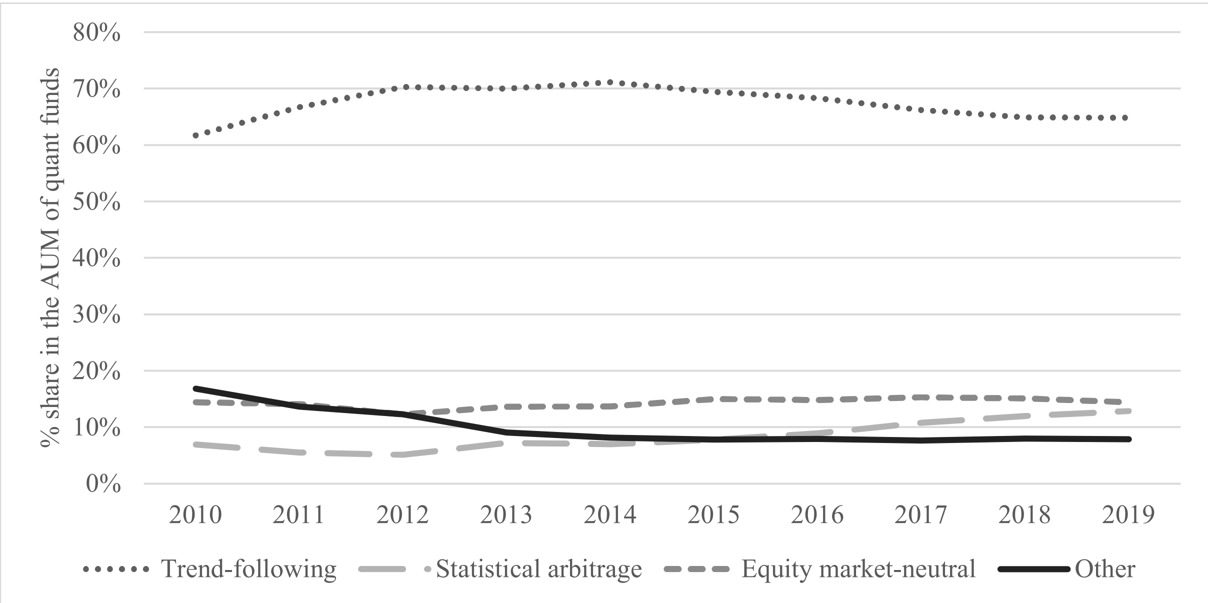

Fig. 2.9. The percentage structure of assets under management of US-domiciled quant hedge funds as at January 31st, 2019, according to Morningstar, Morgan Stanley Research. Source: Author's own study based on Wigglesworth (2019).

Referring to Figure 2.8., assets managed by all four distinguished categories of US-domiciled quant hedge funds tended to increase in presented period of 2010-2019. Trend-following, statistical arbitrage, equity market-neutral and other strategies rose by 9.80% (trend-following), 16.96% (statistical arbitrage), 9.16% (equity market-neutral), 0.31% (other strategies) CAGR, respectively. Total assets managed by all US-domiciled quant hedge funds rose by 9.20% CAGR.

Referring to Figure 2.9., the structure of assets managed by US-domiciled quant hedge funds (considering the strategy type applied) did not change much over the years. The share of the equity market-neutral strategy remained stable, oscillating around 14%. The most significant changes occurred for other strategies, whose share decreased for the benefit of statistical arbitrage strategy (mainly) and trend-following strategy. Trend-following strategies remain the ones, with the biggest share in assets managed by US-domiciled quant hedge funds, oscillating between 62% and 71%, with an average share of 67%. Their share increased from 62% in 2010 to 71% in 2014, and then decreased to 65% in 2019. However, the dynamics of the downward trend was slowing down each year. Again, due to a significant share of US-domiciled quant hedge funds in the AUM of global quant hedge fund industry and a similar growth rate, it can be supposed that US-domiciled quant hedge fund industry is responsible for shaping trends of global quant hedge fund industry, and thus the structure of global quant hedge fund industry (considering strategy type applied) may be similar.

As presented in Figure 2.1., the share of quant funds in assets managed by the global hedge fund industry oscillated around 29%, reaching almost $1 trillion of AUM in 2018. Assets managed by US-based quant hedge funds only, reached almost $0.43 trillion in 2017 (see Figure 2.6.). The US-based quant mutual funds managed slightly above $0.71 trillion of assets in 2017, which constituted 4.3% of US-based mutual fund industry (see Figure 2.5.). The assets managed by quant funds do not seem to be significant compared to $17.71 trillion of assets managed by US-based mutual fund industry (Mordor Intelligence, 2020). Nevertheless, they constitute a group of investors that contributes most significantly to institutional trading on the US stock markets, according to estimates of the TABB Group, presented by The Economist (2019) (see Figure 2.10.).

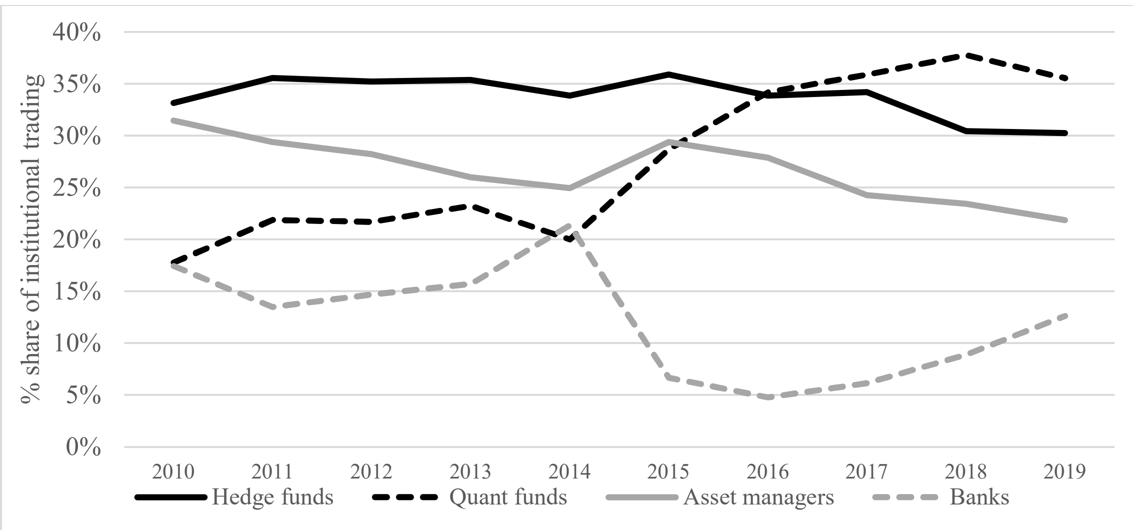

Fig. 2.10. The percentage structure of institutional trading on the US stock markets, taking into account trading volume, excluding retail and high-frequency trading firms. Notes: 2019 is estimated, and asset managers refer to institutions, including pension funds, mutual funds, and other money managers, according to TABB Group. Source: Author's own study based on The Economist (2019).

Over the period 2010-2019, hedge funds, asset managers (institutions including pension funds, mutual funds, and other money managers), as well as banks, lost their share in institutional trading on the US stock markets for the benefit of quant funds, whose share rose from nearly 18% in 2010 to about 35% in 2019. Over a 10-year period presented in Figure 2.10., hedge funds, asset managers and banks lost respectively about 3, 10 and 5 percentage points of their contribution to institutional trading on the US stock markets. The shares of hedge funds and asset managers were in a long-term downward trend, as opposed to quant funds, whose share increased in the long term. The share of banks in institutional trading on the US stock markets has increased since 2016.

Other estimates of the TABB Group, presented by Zuckerman, Levy, Timiraos, and Banerji (2018), pertain to the percentage share of quant hedge funds and retail funds in trading volume (this time not only institutional trading as in Figure 2.10.) on the US stock markets. Estimates are presented in Figure 2.11. According to them, the share of quant hedge funds increased from nearly 14% in 2010 to nearly 29% in 2018, overtaking retail funds. The increase of share that belongs to retail funds and its dynamics was much lower. The share of retail funds increased from about 24% in 2010 to about 28% in 2018.

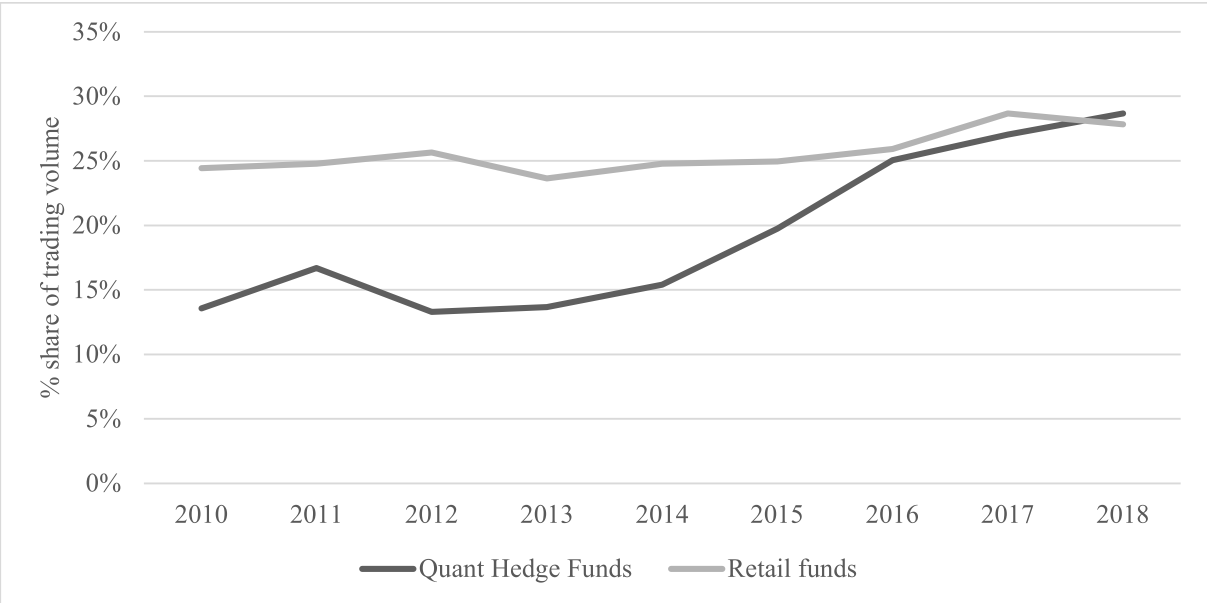

Fig. 2.11. The percentage share of quant hedge funds and retail funds in trading volume (this time not only institutional trading as in Figure 2.10.) on the US stock markets, according to the estimates of the TABB Group. Source: Author’s own study based on Zuckerman, Levy, Timiraos, and Banerji (2018).

Wigglesworth (2019) presented yet other estimates prepared by the TABB Group which pertained to the percentage share of retail investors, mutual funds, hedge funds, quants, HFT market makers, and independent HFTs in the US equity trading volume. Estimates are presented in Figure 2.12.

According to Figure 2.12., the share of quants in US equity trading volume had a clear upward trend and increased from nearly 7% in 2010 to nearly 18% in 2018. Among the other categories of market participants, mentioned in Figure 2.12., two of them had a clear downward trend in the share of trading volume on the US stock markets, namely HFT market-makers and independent HFTs. The share of HFT market-makers decreased from about 39% in 2010 to 31% in 2018. The share of independent HFTs decreased from about 18% in 2010 to 7% in 2018. The other categories mentioned did not change so significantly.

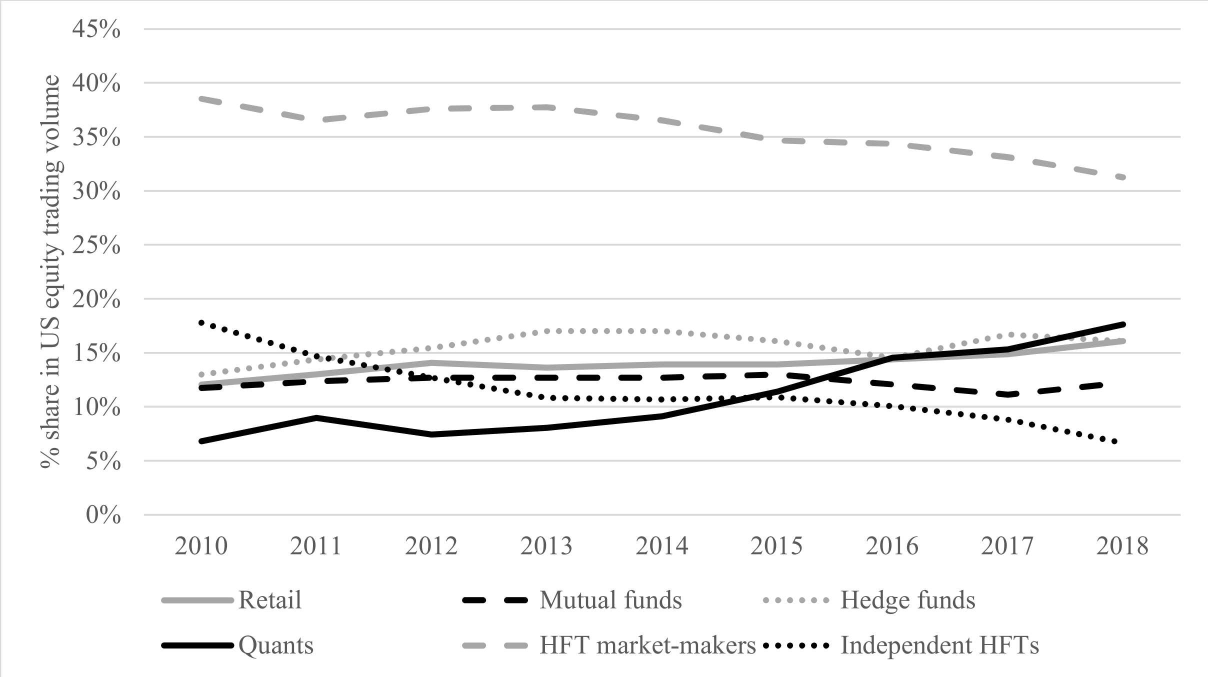

Fig. 2.12. The percentage share of retail investors, mutual funds, hedge funds, quants, HFT market makers, and independent HFTs in the US equity trading volume, according to the estimates of the TABB Group. Source: Author's own study based on Wigglesworth (2019).

2.2. Quantitative trading as a part of the algorithmic trading industry and the importance of algorithmic trading to financial markets

According to Narang (2013), quantitative traders are responsible for the majority of orders sent by trading algorithms. This suggests that in practice the concept of algorithmic trading is highly related to the concept of quantitative trading. This section presents some widely accessible data pertaining to the contribution of algorithmic trading and high-frequency trading to trades made on financial markets. It also makes an attempt to find if the aforementioned data allow to confirm the thesis of Narang (2013), stating that quantitative traders are responsible for the majority of trades generated by algorithms.

Dehod (2019) uses estimates provided by the Aite Group, Goldman Sachs Global Investment Research, depicted in Figures 2.13. and 2.14., which present the market share of algorithmic trading in daily trading volume on the world's markets across different asset classes and regions.

Figure 2.13. presents the estimated percentage market share of algorithmic trading in the daily trading volume on the world's markets, across different asset classes.

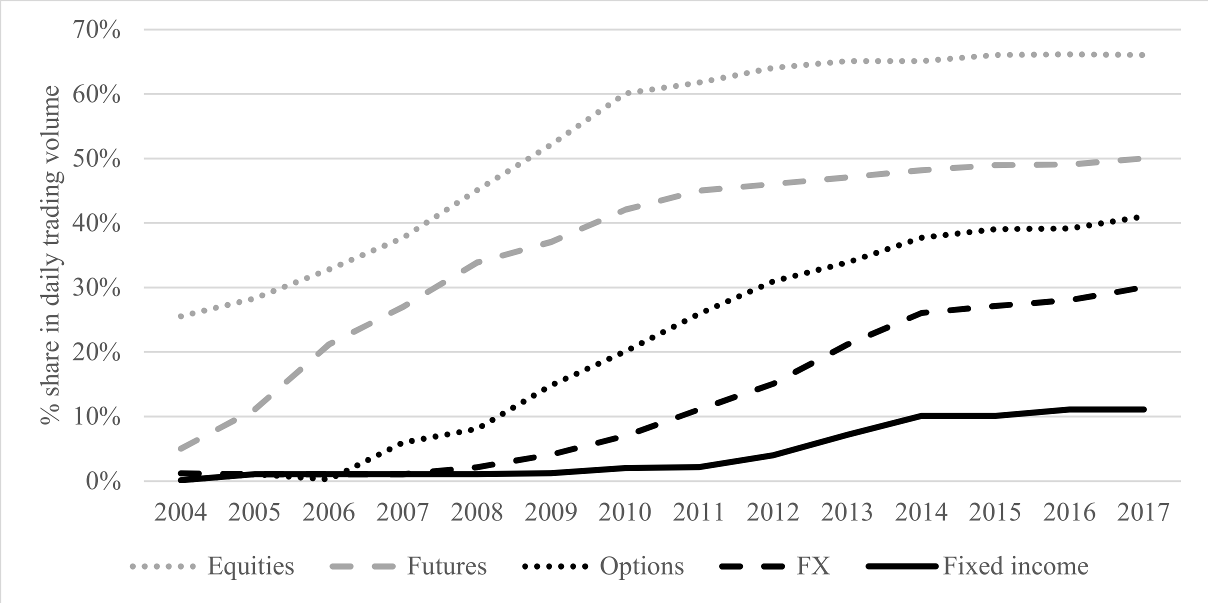

Fig. 2.13. The percentage market share of algorithmic trading in daily trading volume on the world's markets, across different asset classes, estimated by the Aite Group, Goldman Sachs Global Investment Research. Source: Author's own study based on Dehod (2019).

Estimates provided by Aite Group suggest that algorithmic trading systematically gains market share in daily trading volume on the world's markets across different asset classes. However, the dynamics of these gains seems to decrease for all asset classes. In the case of equity and foreign exchange markets, up to 2010 and 2014, respectively, the curves pertaining to the share of algorithmic trading in daily trading volume clearly increased exponentially.

The greatest contribution of algorithmic trading to trading volume can be observed in the case of equity markets. The share of algorithmic trading in daily trading volume on the world's equity markets reached nearly 70% in 2017, while its share in 2004 exceeded barely 25%. The share of algorithmic trading in the futures markets exceeded 50% in 2017, whereas in 2004 its share was estimated to just be 5%. The share of algorithmic trading in the options market rose from less than 1% in 2004 to a little more than 40% in 2017. When it comes to the foreign exchange markets, the share of algorithmic trading increased from barley more than 1% in 2004 to 30% in 2017. The lowest contribution of algorithmic trading to trading volume can be observed for fixed income securities markets. Similarly as in the case of the options market, the share of algorithmic trading in 2004 was estimated at less than 1%. In 2017 it was estimated at about 11%.

Figure 2.14. presents the estimated percentage market share of algorithmic trading in the daily trading volume on the world's markets, across different regions. Except for the Asian markets, algorithmic trading seems to increase its market share from year to year more slowly. A similar conclusion could be drawn from the analysis of curves related to the share of algorithmic trading across different asset classes (see Figure 2.13.).

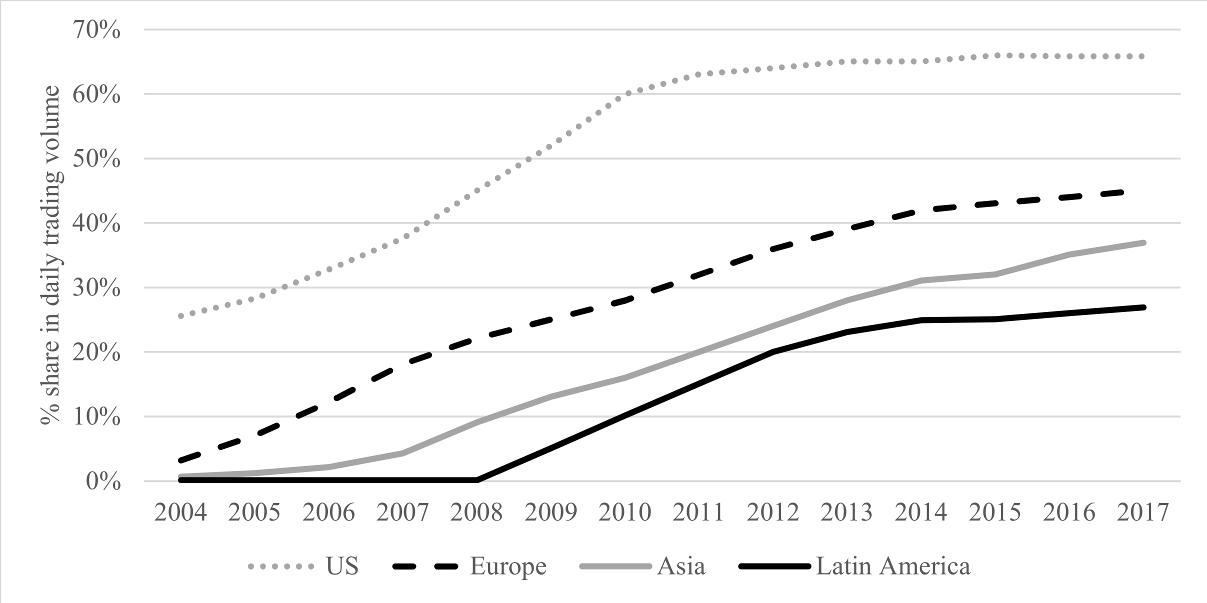

Fig. 2.14. The percentage market share of algorithmic trading in daily trading volume on the world's markets, across different regions, estimated by Aite Group, Goldman Sachs Global Investment Research. Source: Author's own study based on Dehod (2019).

The US markets are the ones with the biggest share of algorithmic trading among all markets examined. Up to 2010, the share of algorithmic trading on the US markets increased exponentially, then logarithmically. Curves pertaining to the other markets suggest that the increase of share of algorithmic trading was rather logarithmic. Thus, the dynamics of expansion of algorithmic trading was more and more slow. The participation of algorithmic trading on the European markets increased from about 3% in 2004 to about 45% in 2017. On Asian markets, algorithmic trading was barely observable in 2004. In 2017, the share of algorithmic trading was estimated to be slightly more than 35%. Moving onto the Latin American markets, the share of algorithmic trading share was near zero by 2008. In 2017 it was estimated to be about 27%.

Moving onto the data related to the contribution of high-frequency trading to the trading volume, Figure 2.15. presents the percentage share of HFT market makers and independent HFTs in the US equity trading volume, according to the estimates of the TABB Group, utilized by Wigglesworth (2019). Figure 2.15. was prepared on the basis of Figure 2.12. Only curves pertaining to HFT market makers and independent HFTs have been left. In other words, Figure 2.15. shows the contribution of HFT market participants (only) to the trading volume generated on the US equity markets. Additionally, the curve representing all HFTs has been added.

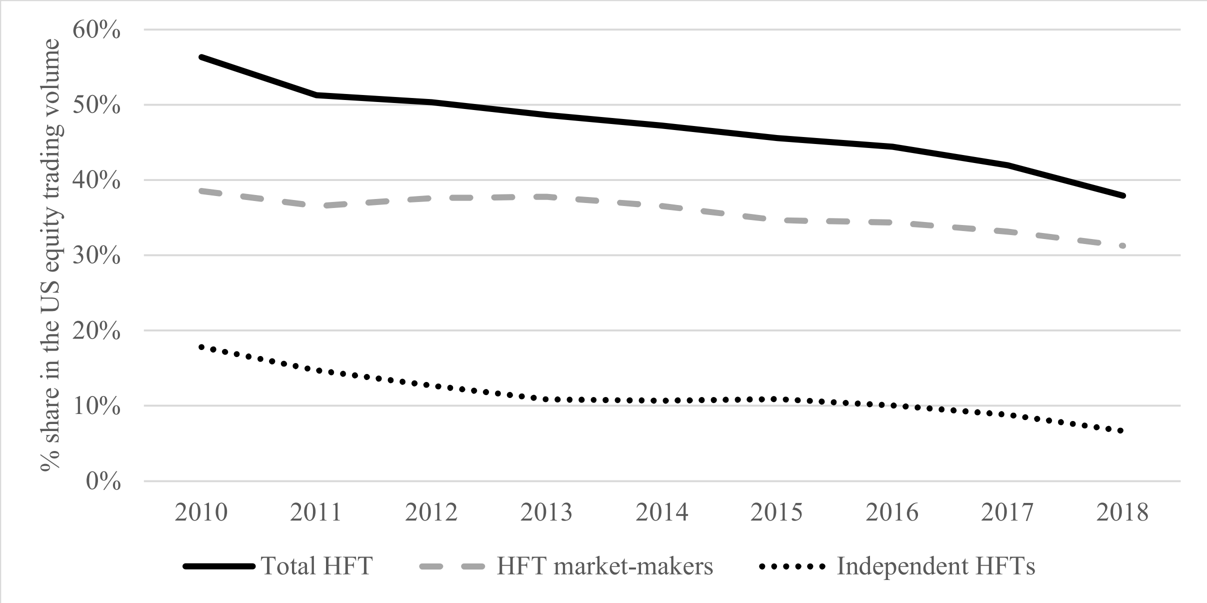

Fig. 2.15. The percentage share of HFT market-makers and independent HFTs in the US equity trading volume, according to the estimates of the TABB Group. Source: Author's own study based on Wigglesworth (2019).

Data pertaining to the share of high-frequency trading in trading volume on the US equity markets, provided by the TABB Group and presented by Wigglesworth (2019), suggest that the total share of high-frequency trading systematically decreases, more or less at an even pace. The share of all HFTs dropped from about 56% in 2010 to about 38% in 2018. Both considered HFT categories, i.e., HFT market-makers and independent HFTs, systematically lose their share in trading volume on the US equity markets. However, the loss of shares over the examined period was greater in the case of independent HFTs.

Detrixhe (2019) presented another composition of high-frequency trading that generated trading volume on the US equity markets, estimated by the TABB Group. Figure 2.16. presents the percentage share of quants, banks, HFTs, and market makers in trading volume generated on the US equity markets. The Tabb Group estimates presented in Figure 2.16. are different from the estimates presented in Figure 2.15., especially since 2014. According to Figure 2.16., a decreasing share of high-frequency trading (from about 55% in 2010) started to recover from the level of around 45% in 2014, i.e., the lowest one in the examined time period. On the other hand, according to Figure 2.15. the share of high-frequency trading continued to fall after 2014.

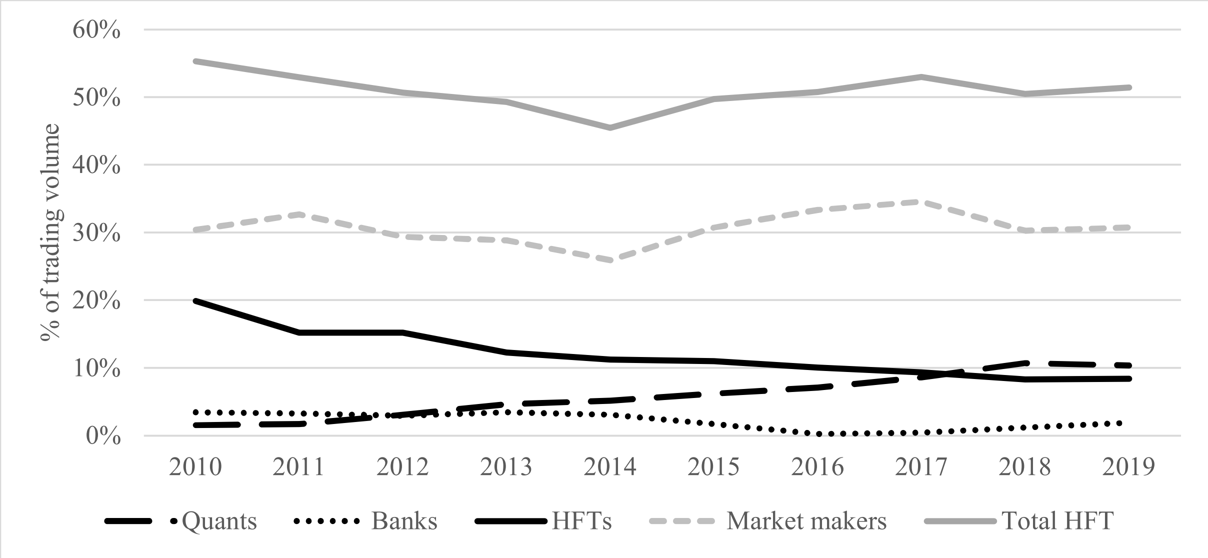

Fig. 2.16. The composition of trading volume generated by high-frequency trading on the US equity markets, estimated by the TABB Group. The percentage share of quants , banks, HFTs and market makers in the trading volume generated on the US equity markets. Source: Author's own study based on Detrixhe (2019).

Other differences between the estimates of the TABB Group, which have been presented in Figures 2.15. and 2.16., refer to the share of market-makers and independent HFTs. Estimates presented in Figure 2.16. suggest that the share of market-makers oscillated around 31% with a more significant drop in 2014 to about 26% and an increase in 2017 to about 35%. The drop mentioned above, which occurred in 2014, led to a decline of the entire HFT industry in the same year. The share of independent HFT traders dropped from nearly 20% in 2010 to less than 10% in 2019. The largest differences between the estimates presented in Figures 2.15. and 2.16. are related to market-makers. According to Figure 2.15. their share constantly decreased over the examined time period. The decrease started from a much higher level compared to the estimates presented in Figure 2.16. The share of banks dropped from about 3% in 2010 to be barely observable in 2016. Since then, they have started to recover. As the only group of HFT traders, the quants clearly increased their participation in trading volume generated on the US equities markets. Their share rose from about 2% in 2010 to about 10% in 2019.

Figure 2.17. presents the same composition of trading volume generated by high-frequency trading on the US equity markets as Figure 2.16. However, this time, trading volume generated by all high-frequency traders is 100%. This form of data presentation enables us to see even more clearly how particular HFT traders contributed to the trading volume generated by high-frequency trading.

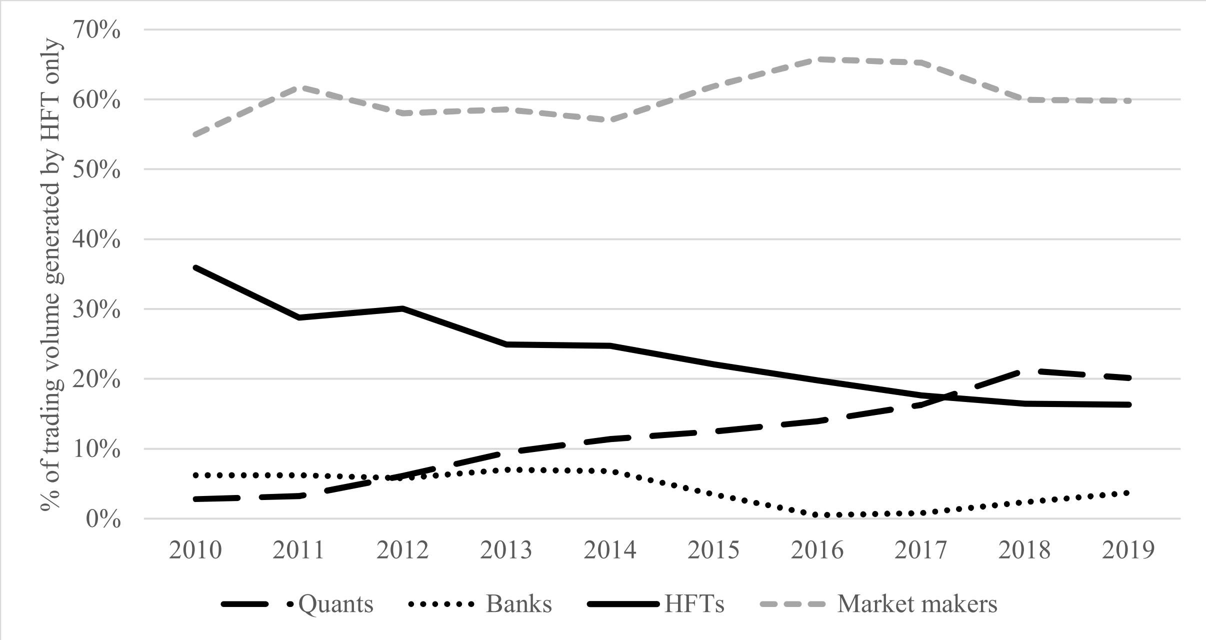

Fig. 2.17. The composition of trading volume generated only by high-frequency trading on the US equity markets, estimated by the TABB Group. The trading volume generated by all high-frequency traders constitutes 100% here. Source: Author's own study based on Detrixhe (2019).

Unlike Narang (2013), the estimates of the TABB Group presented in Figure 2.17. suggest that quantitative traders (quants) do not contribute to the majority of trading volume generated by high-frequency traders. However, such a discrepancy may be related to differences in definitions adopted by Narang (2013) and the TABB Group. The contribution of quantitative traders to algorithmic trading is probably even lower. However, widely accessible estimates do not indicate directly the contribution of quantitative traders to trading volume generated by algorithmic trading. They also do not directly indicate what part of algorithmic trading is generated by high-frequency trading.

According to estimates presented in Figure 2.17., the share of quantitative traders in the trading volume generated by high-frequency traders on the US equity markets continues to grow, from about 3% in 2010 to about 20% in 2019. It can only be assumed that the share of quants in trading volume generated by algorithmic traders is even lower. The share of market-makers oscillated around 60%. Again, the share of independent HFT traders decreased significantly, from around 36% in 2010 to about 16% in 2019. The share of banks collapsed from about 6% in 2010 to barely be observable in 2016. Starting from 2016 it tries to recover.

Even though the author of this thesis could not collect any widely available estimates indicating how high-frequency trading contributed to trading volume generated by algorithmic trading, an attempt was made to estimate it using the estimates of the TABB Group, presented in Detrixhe (2019), Massoudi and Stafford (2014) (estimates pertaining to the share of high-frequency trading in trading volume on the US equity markets), as well as using estimates presented by Glantz and Kissell (2014) (estimates pertaining to the share of algorithmic trading in trading volume on the US equity markets in years 2005-2012). The estimates mentioned above, presented by Detrixhe (2019), Massoudi and Stafford (2014), Glantz and Kissell (2014) are presented in Figure 2.18. Additionally, the percentage share of algorithmic trading in trading volume on US equity markets was estimated in years 2013-2019 using a logarithmic function. The function was estimated on the basis of the share of algorithmic trading in daily trading volume on the US markets, presented in Figure 2.14. It should be noted that the data presented in Figure 2.14. referred to many different asset classes. Not only to equities.

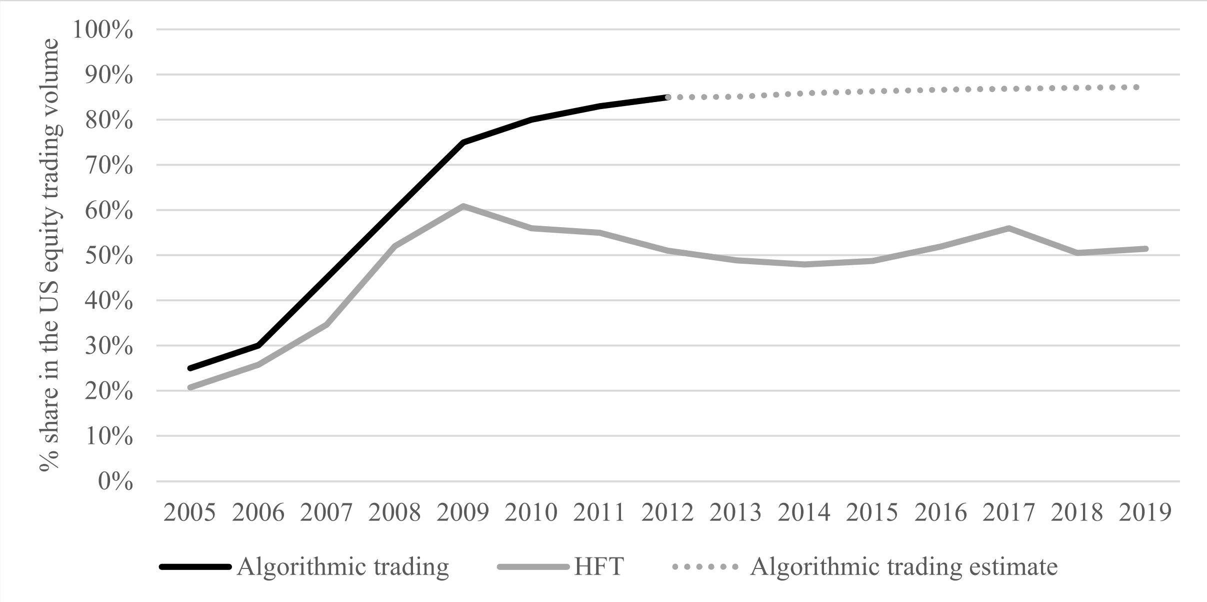

Fig. 2.18. The percentage market share of high-frequency trading (HFT) and algorithmic trading in trading volume on the US equity markets. The share of HFT in the entire research period and algorithmic trading in the period 2005-2012 was estimated by the TABB Group. The share of algorithmic trading starting from 2013 was estimated by the author of this thesis using a logarithmic function estimated on the basis of the share of algorithmic trading in daily trading volume on US markets, presented in Figure 2.14. Source: Author's own study based on Detrixhe (2019), Massoudi and Stafford (2014), Glantz and Kissell (2014).

The data presented in Figures 2.17. and 2.18. constituted the basis for estimation of the share of high-frequency trading in the trading volume generated by algorithmic trading on the US equity markets. Additionally, data presented in Figures 2.17. and 2.18. allowed to estimate the share of quants in trading volume on the US equity markets generated by high-frequency trading and algorithmic trading. The results of estimations are presented in Figure 2.19.

The estimates presented in Figure 2.19. suggest that the share of high-frequency trading in trading volume generated by algorithmic trading on the US equity markets systematically declined from around 70% in 2010 to about 56% in 2014. In the following years, the share of HFT recovered to reach a level of 64% in 2017 and to fall again below 60% in the following years.

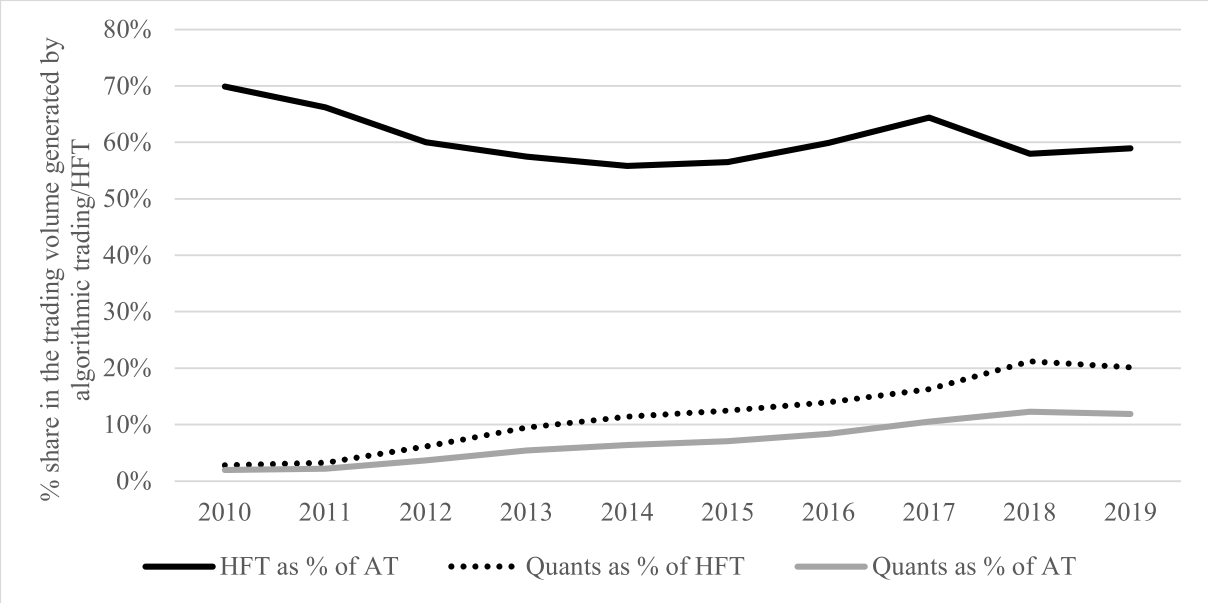

Fig. 2.19. The share of HFT in the trading volume generated by algorithmic trading (AT) on the US equity markets. The share of quantitative trading (quants) in the trading volume generated by HFT and algorithmic trading on the US equity markets. Estimates based on data presented in Figures 2.17. and 2.18. Source: Author's own study.

The share of quantitative trading in the trading volume generated by algorithmic trading on the US equity markets increased systematically, similarly to the share of quantitative trading in the trading volume generated by high-frequency trading. The contribution of quantitative trading to the trading volume of algorithmic trading rose from approximately 2% in 2010 to approximately 12% in 2019. The contribution of quantitative trading to the trading volume of high-frequency trading increased from about 3% in 2010 to about 20% in 2019.

The other time frames for the TABB Group estimations have been presented in Figure 2.20., which contains estimates pertaining to the percentage share of high-frequency trading in trading volume on the US and European equity markets. Estimates come from the article by Massoudi and Stafford (2014).

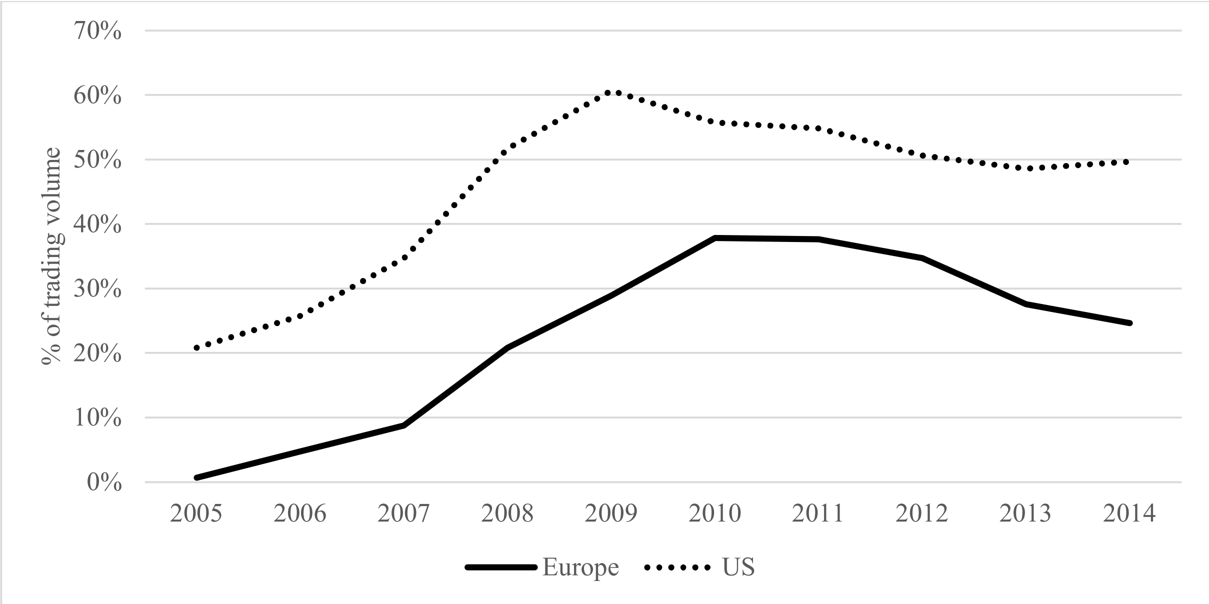

Fig. 2.20. The percentage share of high-frequency trading in trading volume on the US and European equity markets, estimated by the TABB Group. Source: Author's own study based on Massoudi and Stafford (2014).

The upward trend of share of HFT on the US markets changed in 2009 to a downward one. By 2009, the share of HFT increased exponentially. On European markets, the share of HFT increased by 2010. Since then, it has also been in a downward trend. The expansion of HFT lasted 1 year longer on the European markets. On the US equity markets, HFT contributed to about 20% of trading volume in 2005. In 2009, its share reached its highest level, estimated to be about 60%. In 2014 it reached nearly 50%. The contribution of HFT to the trading volume generated on the European markets was barely visible in 2005. The TABB Group estimated that HFT on the European markets reached its highest share in 2010 and was estimated at about 38%. Its share fell to about 25% in 2014.

Sapir (2019) made an attempt to explain the changes in share of HFT in trading volume on the US equity markets, estimated by the TABB Group, with the changes in VIX. VIX, i.e., the CBOE Volatility Index is calculated and published in real time by the Chicago Board Options Exchange. VIX reflects expectations as to volatility of the stock market, based on S&P 500 index options. It is also commonly called a fear index or a fear gauge.

Figure 2.21. presents the percentage share of high-frequency trading in trading volume on the US equity markets, estimated by the TABB Group. Figure 2.21. also presents the CBOE Volatility Index. A similar shape of both curves may suggest that HFT takes over the market when volatility increases. The occurrence of increasing activity of HFT traders in periods of increasing volatility has been also discussed, for instance, by Zhang (2010), Shafi, Latif, Shad, and Idrees (2019) or Patterson and Osipovich (2020).

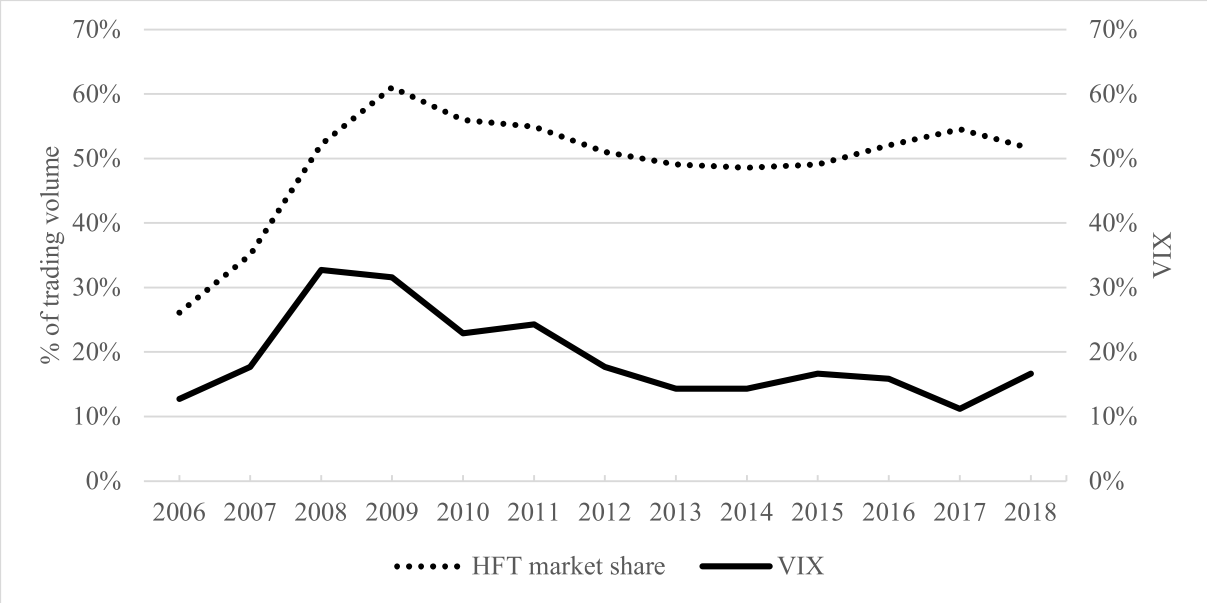

Fig. 2.21. CBOE Volatility Index and the percentage market share of high-frequency trading in trading volume on the US equity markets, estimated by the TABB Group. Source: Author's own study based on Sapir (2019).

A declining volatility on the markets may imply not only a declining activity of HFT traders, but also the decrease of their revenues. Osipovich (2017) made an attempt to reconcile the decreasing revenues of HFT firms generated on the US equity markets, with decreasing market volatility (a decreasing VIX). The cooccurrence of these phenomena is presented in Figure 2.22. With the use of estimates of revenues of HFT firms, provided by the TABB Group, and with the use of VIX, Osipovich (2017) proposed that HFT firms benefit from the volatility of markets.

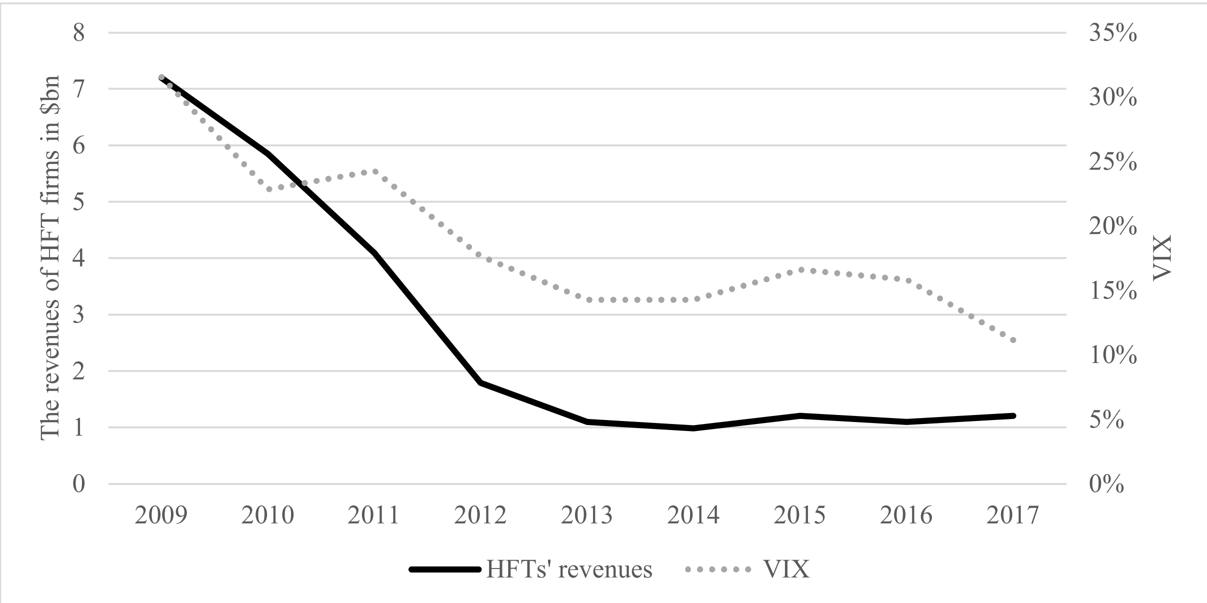

Fig. 2.22. Revenue of HFT firms generated on the US equity markets, estimated by the TABB Group, and the CBOE Volatility Index. Source: Author's own study based on Sapir (2019) and Osipovich (2017).

Grindsted (2018) conducted an in-depth study of literature that contained estimates pertaining to the percentage contribution of high-frequency trading to trading volume on the

US stock markets. The collected data allowed him to provide the lowest and the highest estimates. They are presented in Figure 2.23., together with estimates delivered by the TABB Group. As opposed to well-known estimates of the TABB Group, which suggest, that since 2009 the share of HFT was in a downward trend for many following years, the lowest and the highest estimates suggest that the share of HFT continued to rise after 2009.

The highest estimates proposed by Grindsted (2018) start from a similar level compared to estimates of the TABB Group, namely, from about 23% in 2005. According to the highest estimates, the growth of share of HFT in trading volume on the US equity markets was stopped at the level of about 90% in 2013. After its decline, in 2017 it returned to the level from 2013. According to the lowest estimate, the share of HFT increased from a little more than 10% in 2005, to about 45% in 2017. The longest period of decline of the share of HFT could be observed between 2009 and 2012. However, its drop was not so significant.

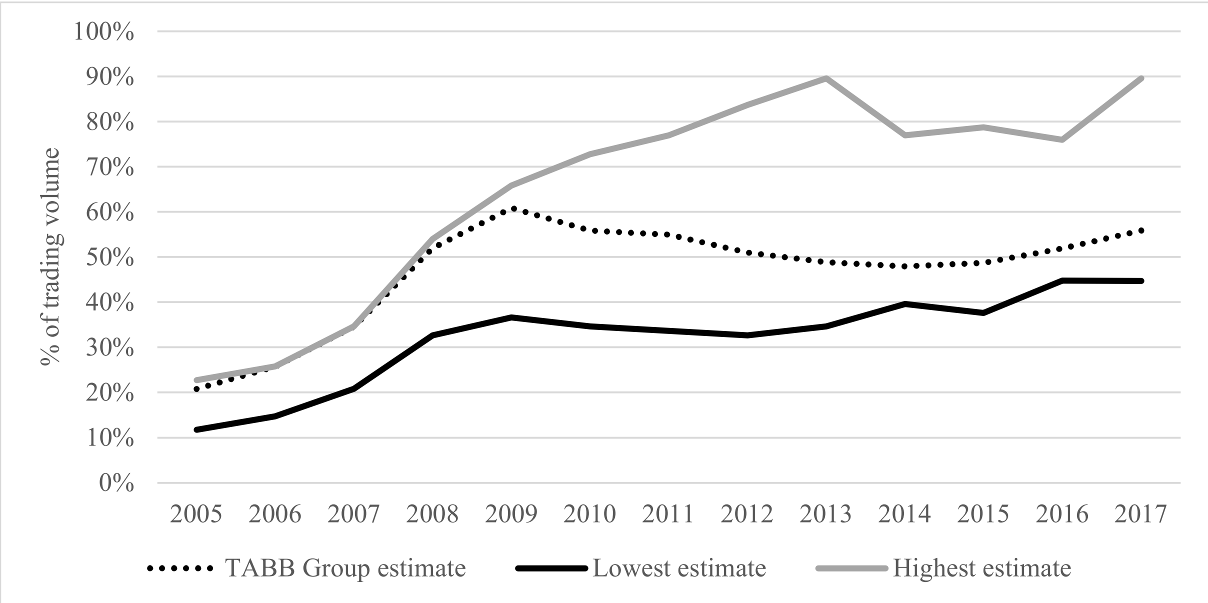

Fig. 2.23. The percentage share of high-frequency trading in trading volume on the US equity markets, estimated by the TABB Group, as well as the lowest and the highest estimates found by Grindsted (2018). Source: Author's own study based on Grindsted (2018).

Data referring to the contribution of high-frequency trading to US equity markets, presented so far, have been expressed in percentage terms, mainly as a percentage share in trading volume. Figure 2.24. presents estimates that break down the average daily trading volume on US equity markets in $ billion, by source. The data have been estimated by the Credit Suisse Trading Strategy and presented by Chaparro (2017).

The curve referring to the average daily trading volume generated by HFT equity market participants, presented in Figure 2.24., resembles the curves from previous figures (e.g., see Figure 2.23.), which refer to the percentage share of HFT in trading volume on the US equity markets. In 2009, i.e., in the period of the greatest dominance of HFT, they generated nearly $6 billion of daily volume on average, while in 2003 volume generated by HFT traders was barely observable. In 2018, HFT was responsible for generating nearly $4 billion of daily volume on average, i.e., about $1.14 trillion more compared to active funds and about $3.12 trillion more compared to passive funds.

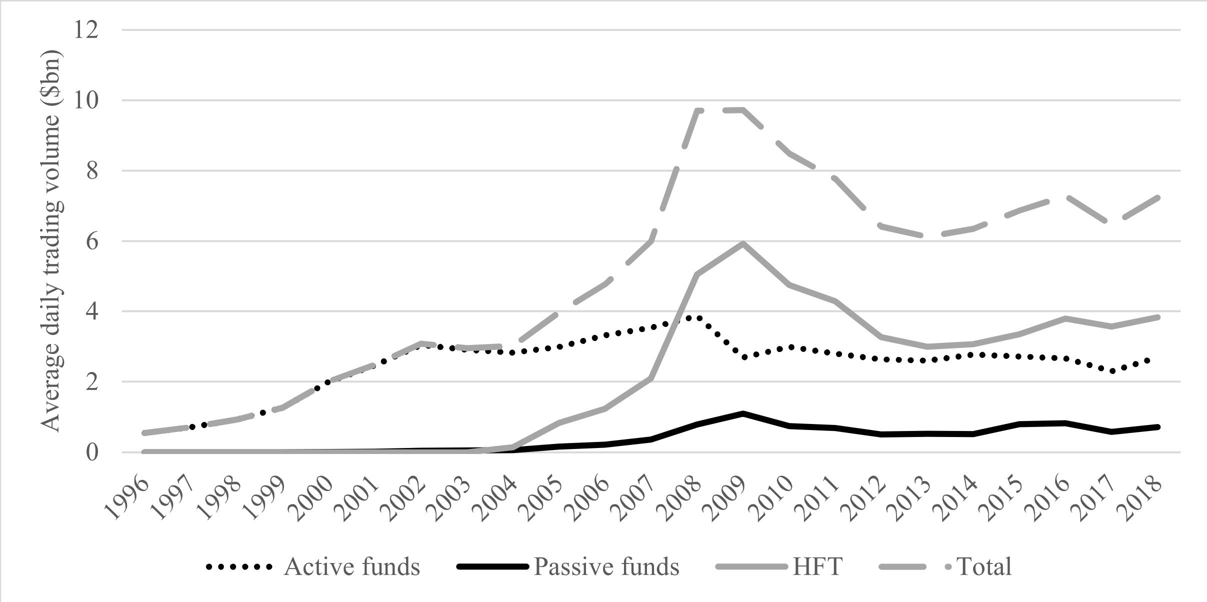

Fig. 2.24. The estimates by the Credit Suisse Trading Strategy, which break down the average daily trading volume on the US equity markets by source, in $bn. Source: Author's own study based on Chaparro (2017).

2.3. The impact of algorithmic trading on financial markets

Algorithmic trading (including high-frequency trading), as a relatively new phenomenon, constitutes a willingly discussed topic, especially when it comes to its impact on financial markets. There may be many reasons for such a big interest in the issue of the impact of algorithmic trading on financial markets, like its rapid expansion, increasing (in many cases, prevailing) share in trading volume, application of the state-of-the-art technology, or the possibility of effecting activities harmful to the markets. Activities taken up by the algorithmic trading market participants are difficult to expect and thus, the regulators decide to regulate and supervise them, in order to ensure that the algorithmic traders do not use their advantages and do not perform any harmful actions to other market participants. The uncertainty related to possible actions taken by the market participants that apply algorithmic trading techniques, encourages researchers to examine the impact of algorithmic trading on financial markets. It also encourages regulators to constantly supervise the actions of algorithmic traders.

Studies raising the issue of the impact of algorithmic trading on financial markets do not bring unambiguous results. Nevertheless, most of them suggest that algorithmic trading is beneficial to financial markets. For example, Zhou and Kalev (2019) provided a comprehensive review of 19 studies on the impact of algorithmic trading on Asia-Pacific markets, published in the years 2011-2017. Zhou and Kalev (2019) focused on investigating the impact of algorithmic trading on such market features as liquidity, price discovery, and volatility. Not all 19 studies investigated the impact of algorithmic trading on all 3 market features mentioned above. 6 studies proposed that algorithmic trading had a positive impact on market liquidity (liquidity increased), and just 2 studies proposed the opposite. 6 studies proposed that algorithmic trading had a positive impact on price discovery (price discovery increased), and just 1 study proposed the opposite. 4 studies proposed that algorithmic trading had a positive impact on market volatility (increased volatility), and just 1 study proposed the opposite. To sum up the literature review of Zhou and Kalev (2019), most studies indicate that algorithmic trading increases market liquidity, price discovery and informational efficiency. However, it also increases market volatility.

Zhou, Elliott, and Kalev (2019) focused on the impact of algorithmic trading on the price discovery only. A comprehensive issue-related literature they conducted confirms conclusions of the abovementioned literature review of Zhou and Kalev (2019). Namely, most studies suggest that algorithmic trading improves the price discovery of financial markets.

Frino, Mollica, Monaco, and Palumbo (2017) instead focused on the impact of algorithmic trading on market liquidity. Their study on Borsa Italiana indicates that algorithmic trading increases market liquidity. Their findings are in line with other studies they discussed in the literature review. Those conclusions confirm conclusions proposed by a very willingly cited and one of the first papers (or even the first one, as the authors mention) on the impact of algorithmic trading on the market quality by Hendershott, Jones, and Menkveld (2011). Their study on the NYSE indicates that algorithmic trading improves liquidity and enhances informativeness of quotes. The opposite results to the majority of issue-related studies have been proposed by Ramos and Perlin (2020) in their study on the Brazilian equities market, where algorithmic trading reduced the liquidity.

Although it seems that there is a general consent regarding the impact of algorithmic trading on market liquidity and price discovery, studies on the impact of algorithmic trading on market volatility propose various conclusions. For instance, 4 out of 5 studies discussed in the abovementioned literature review by Zhou and Kalev (2019), suggest that algorithmic trading increases market volatility. At the same time, Growth (2011) proposes that existing studies suggest that algorithmic trading does not increase the volatility. It is in line with his study on the German Frankfurt Stock Exchange.

2.4. Conclusions

Market estimates presented in this chapter indicate that quantitative funds which operate as both hedge and mutual funds significantly contribute to trading volume generated at least on the US equity markets, despite managing relatively not so large amounts of assets. Considering assets managed by quant funds insignificant can be a little excessive, as they are responsible for managing about 29% of assets of the global hedge fund industry. Nevertheless, the share of quant mutual funds, in a much larger mutual fund industry, is still scarce. However, it constantly increases, at least in the case of the US-domiciled mutual fund industry.

Algorithmic trading is responsible for the most of the trading volume generated on the US and European markets, as well as on the global equity markets. The estimates indicate that the share of algorithmic trading in trading volume, on the global financial markets across different regions and asset classes, still grows. Nevertheless, in most cases, its growth has slower and slower dynamics.

Despite a growing trend of the share of algorithmic trading in the trading volume generated on the world's financial markets, market estimates indicate that, at least on the US and European equity markets, the share of high-frequency trading declines. Some researchers like Zhang (2010), Shafi, Latif, Shad, and Idrees (2019), Patterson and Osipovich (2020) identify a diminishing market volatility as a reason for a decreasing share of high-frequency trading in trading volume. They propose that high-frequency traders exploit market volatility and inefficiency and benefit from it.

As opposed to Narang (2013), the estimates presented in this chapter suggest that quantitative trading is not responsible for the majority of trading volume generated by algorithmic and high-frequency trading. However, its share in the trading volume generated by algorithmic and high-frequency trading regularly increases. In 2019, quantitative trading was responsible for about 20% of trading volume generated by high-frequency trading and about 12% of the trading volume generated by algorithmic trading.

Market estimates utilized in this chapter show that indisputably, quantitative funds, as well as related phenomena such as quantitative and algorithmic trading, are very important to financial markets and their importance still increases. In the case of algorithmic and high-frequency trading and some markets on which algorithmic traders operate, their meaning is even substantial, as they are responsible for the majority of trading volume generated. Moreover, their great impact on various market features such as market liquidity, volatility, and price discovery is well examined in the academic literature.

3. Theoretical background for testing the informational efficiency of quant funds in the context of the weak-form efficiency of the market

The aim of this chapter is to present the concept of the efficient market hypothesis and some commonly applied econometric techniques to test it. In particular, this chapter is focused on the weak-form efficient market hypothesis. The material presented in this chapter constitutes a background for developing the methodology of verification of a supplementary research hypothesis H2, which states that the weak-form informational efficiency of quantitative funds is higher than the weak-form informational efficiency of qualitative funds. Methodology developed on the basis of the knowledge presented in this chapter will also be used to answer some supplementary research questions posed in the introduction. In addition, the aforementioned methodology will be used to evaluate the applicability of some performance measures that require normality of returns. Furthermore, it will allow to indicate the periods of a low weak-form informational efficiency of equity markets (the selected benchmarks of examined investment funds), which will be used in the study on performance of quantitative funds aiming to verify hypothesis H3. This supplementary hypothesis states that quantitative funds perform better than qualitative funds in periods of a low weak-form informational efficiency of equity markets. The non-rejection of the weak-form efficiency hypothesis, with regard to examined quant funds, will allow for stating that the forecasting of returns of quantitative funds on the basis of their historical performance does not bring abnormal profits. Econometric tools presented in this chapter will allow to determine some features of returns of quant funds within the context of the weak-form informational efficiency. Thus, tools presented in this chapter will allow to examine the forecasting features of returns of quant funds, and the possibility to generate abnormal profits from investment in quant funds on the basis of their historical returns.

3.1. The concept of the efficient market hypothesis

The forecasting of future value of fund participation unit can be treated as the test of the efficient market hypothesis (EMH). According to EMH, there is no possibility to forecast financial asset prices or returns on the basis of their historical values (weak-form EMH), any publicly available information (semi-strong EMH), and any private as well as confidential information (strong EMH). The efficient market hypothesis is related to the concept of informational efficiency. The efficiency of the market in the informational context refers to the speed and accuracy of dissemination of information and its incorporation into the prices of financial assets. Among the information relevant for shaping of financial asset value, the following information types can be distinguished (Witkowska, Matuszewska-Janica, & Kompa, 2012):

- macroeconomic – information pertaining to the basic characteristics of national economy and related foreign economies,
- sectorial – information pertaining to sector that is related to a given asset,

- specific – information pertaining to the issuer of a given asset.

The efficient market hypothesis was first proposed by Bachelier in 1900 and then advanced in the literature by such researchers as Fama (1970), who is often credited with providing a constructive definition of the efficient market hypothesis. In the first significant book raising the issue of quantitative description of financial asset prices, published in 1900, Bachelier came to the conclusion that the increments of the French bond prices had to be independent random variables described by the same normal distribution with a zero expected value and a constant variance. This statement by Bachelier, tantamount to proposing the hypothesis of random walk, became the basis of the efficient market hypothesis in the informational context. Nevertheless, the theses of Bachelier were forgotten for the following several decades. Starting from about 1937 when Cowles and Jones analysed the increments of prices on the stock exchange in New York, researchers commonly began to conduct their studies on the compatibility of the empirical time series with the random walk hypothesis. At the very beginning, the issue-related studies tested the hypothesis which stated that there was no autocorrelation in the increments of asset prices. The conclusions were different. However, even when autocorrelation occurred, it seemed too low to accurately forecast price changes. Then, starting from the early 1960s, the researchers began to apply other methods to test the independence of returns, like the series tests, filters generating buy and sell signals, and spectral analysis-based methods. Most studies could not reject the hypothesis of independence of price changes. In 1963 Mandelbrot began a new chapter in issue-related studies. He pointed out a well-known but often ignored fact and proposed that the empirical distributions of the first and further price changes have usually fat tails and deviate from a normal distribution. This fact stands in contradiction with the random walk model proposed by Bachelier. Mandelbrot suggested that there is one of three possibilities: price increments are not independent, price increments do not have the same distribution, and price increments do not have a normal distribution. Mandelbrot proposed to replace the normal distribution with a class of stable distributions, which constitute a natural generalization of the normal distribution. Application of this group of distributions could contribute to holding an assumption of equal distributions of increments of asset prices and even of their independence. However, studies on the application of stable distributions were marginalised and not continued because of analytical difficulties that consisted in the inability to define unambiguously a density function of most stable distributions. A fact pointed out by Mandelbrot is just one of the stylized facts pertaining to financial time series which can be defined as a set of features of a given statistical object. Some best examined stylized facts pertaining to returns of financial assets have been listed by Czekaj (2014):

- linear autocorrelations are statistically significant only for short time scales, usually shorter than 20 minutes, where the market microstructure effects occur. For longer time scales the linear autocorrelations are statistically insignificant, and even when the autocorrelation occurs, it is too low to forecast the price changes accurately;

- a Gaussian character of distribution of returns of financial assets applied in many financial assets pricing theories, seems not to describe well the empirical financial time series due to fat tails and other deviations from the normal distribution. The unconditional distribution of financial asset returns seems to have tails of a Pareto type (power-law probability function) which suggests that the extreme losses and gains occur more often than in the normal distribution;
- there is an asymmetry between the losses and gains for the benefit of losses which exceed gains. The outstanding losses are not compensated with equally large gains;
- distribution of empirical returns is more compatible with the normal distribution for increasing time scale for which the returns are calculated, i.e., an aggregated normality occurs;
- variance concentration and returns intermittence;
- a slow decline of the autocorrelation function of the unconditional returns, i.e., the persistence;
- a negative correlation between returns and volatility, i.e., the leverage effect;
- correlation between volatility and volume.

Doubts formulated by Mandelbrot were clarified by Samuelson in 1965, who presented a relation between informational efficiency of the market and the martingale theory. According to Samuelson, the increments of financial asset prices create a fair game, i.e., the increments of prices still have independent normal distributions but with unequal variances. It means that the prices are martingales, and the returns are martingale differences. After the publication of paper by Fama in 1970, this version of the informational efficiency has been approved by a wide body of scientists and is respected nowadays.

According to Fama (1970), an informationally efficient market has to fulfil the following criteria:

- the lack of transaction costs and taxes,
- a common and equal access to information,
- the same way of assessing the impact of information on financial asset prices by all market participants.

Due to inability to fulfil the above-mentioned conditions in practice, the following features are assumed to characterize the informationally efficient market (Witkowska, Matuszewska-Janica, & Kompa, 2012):

- a large number of market participants,
- financial assets have parameters which enable the market participants to compare them,
- a common and equal access to information to all market participants,
- a random character of new information inflow, except for information whose publication date is planned in advance, and the publication date is provided by regulations.

Haugen (1996) proposes the following features of the efficient market:

- financial asset prices adjust to new information quickly and adequately,
- changes in the price of financial assets are random,
- transaction rules and systems used in the simulation experiments do not generate averagely higher returns,
- professional investors cannot generate averagely higher returns.

Osińska (2006) enumerates the following assumptions of the informationally efficient market:

- changes in the price of financial assets are minimal,
- a daily number of transactions made on the market is finite and insignificant,
- a relation between the price and value is the most important determinant of return,
- choosing a financial asset which has a chance of generating a higher profit (in the case of comparison of assets with different expected returns), should be considered a logical decision,
- chances of entering into transaction are low when generating profit by buyer and seller is not possible. Transactions are made at the equilibrium price determined on the basis of information available at a given moment, and it is due to the ability of investors to reflect the value in the price,
- the prices are adjusted to the information available at a given moment. Thus, consecutive price changes are independent,
- due to the independence of the price changes, it can be expected that the distribution of the price changes will be a normal distribution with a stable expected value and a finite variance.

According to the assumptions mentioned above, on the informationally efficient market, the prices reflect all information available at a given moment. Assuming that all known information is discounted in the current financial asset price, the informationally efficient market reacts to a new information only when the new information implicates the change in the expected value of the price (Witkowska, Matuszewska-Janica, & Kompa, 2012).

3.2. Three levels of the informational efficiency of the market

Taking into account a set of information possessed, Fama (1970) distinguished three different types of the informational efficiency of the market, namely, a weak form, a semi-strong form, and a strong form (Miziołek, 2013):

- weak-form efficiency states that the current price of the financial asset fully reflects information from the historical prices. Therefore, investors cannot forecast the subsequent prices and gain abnormal profits applying strategies based on past prices.

Thus, according to the efficient market hypothesis in a weak form, a technical analysis cannot provide the investor with abnormal returns;

- semi-strong-form efficiency assumes that the current price of the financial asset fully reflects not only the information from the historical prices but also all currently, and publicly available information like the macroeconomic news, earnings forecasts, financial reports, or the press information. According to the efficient market hypothesis in a semi-strong form, there is no possibility to earn abnormal profits using publicly available information only;
- strong-form efficiency assumes that the current price of the financial asset fully reflects not only the information from the historical prices and publicly available information, but also confidential and private information. According to the efficient market hypothesis in a strong form, not only market participants who use publicly available information, but also investors who possess confidential and private information are not able to earn abnormal profits because the market will recognise information coming from the attempt to make transaction based on a confidential or private knowledge.

Figure 3.1. presented below illustrates the levels of the informational efficiency of the market relativized depending on the information set possessed. Figure 3.1. emphasizes a particularly important relationship between the information sets used in three variants of the efficient market hypothesis.

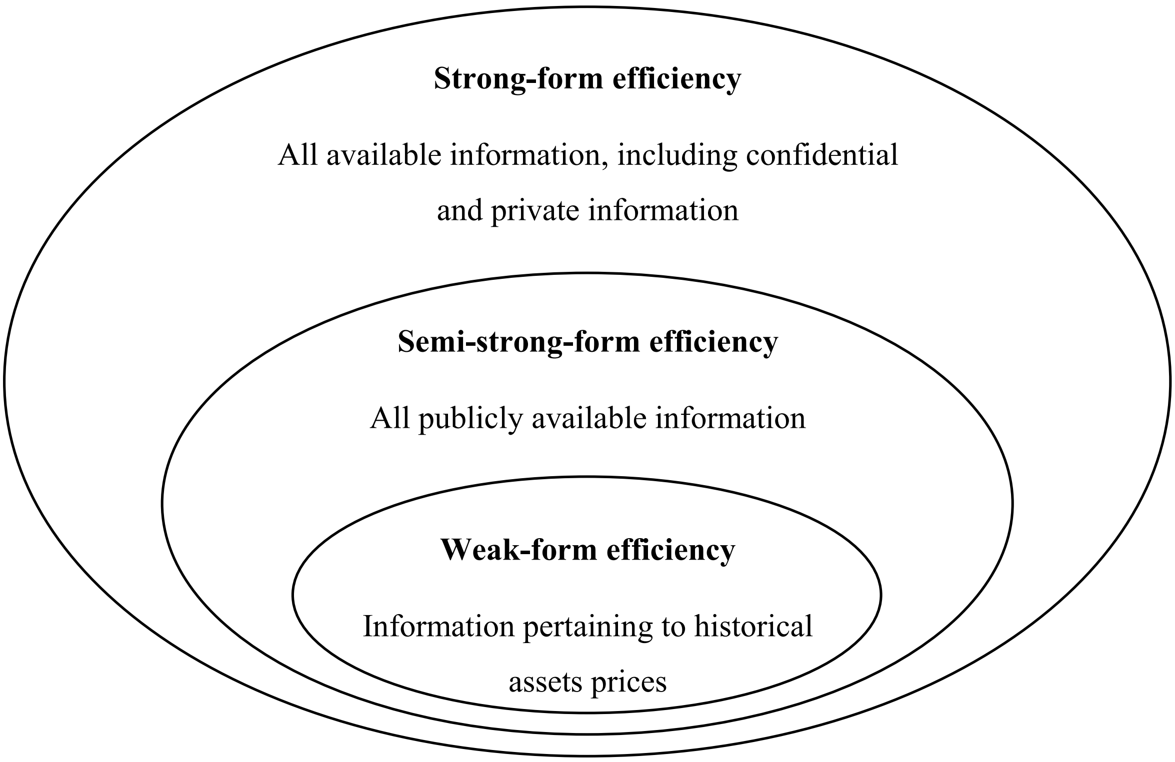

Fig. 3.1. The levels of the informational efficiency of the market relativized depending on the information set possessed. Source: Author's own study based on Witkowska, Matuszewska-Janica and Kompa (2012)

The term ‘abnormal profits’ used in the above-mentioned definitions of different types of informational efficiency, refers to the difference between the actual return and the so-called ‘normal return’. The term ‘normal return’ refers to a theoretical return delivered by an asset pricing model. The problem is that, different asset pricing models return different normal returns. The abnormal return forecasts are made on the basis of particular information set depending on the form of informational efficiency. The market efficiency hypothesis is not rejected when abnormal returns cannot be forecasted, behaving randomly in this sense. The normal or required return R_t^* over a time interval $[t, T]$, for any $T > t$, calculated with an asset pricing model, can be formulated as follows (Linton, 2019):

$$R_t^* = R_{ft} + \pi_t, \tag{3.1}$$

where:
R_{ft} – risk-free rate at time t,
π_t – risk premium at time t.

The risk premium constitutes a compensation of a risk-averse investor for taking risk. The risk premium as the component of the normal return is delivered by an asset pricing model. According to the efficient market hypothesis, on average, an investor cannot generate a higher return than R_t^*.

Under the null hypothesis $\mathcal{F}_t$ (the efficient market hypothesis), it holds that the return R_t realized over the same time interval satisfies the following:

$$E(R_t|\mathcal{F}_t) = R_t^*. \tag{3.2}$$

Depending on the form of the market efficiency hypothesis, $\mathcal{F}_t$ contains a different set of information. In the case of:

- the weak-form efficient market hypothesis, $\mathcal{F}_t$ contains only information on historical prices,
- the semi-strong-form efficient market hypothesis, $\mathcal{F}_t$ contains publicly available information at time t,
- the strong-form efficient market hypothesis, $\mathcal{F}_t$ contains publicly available information at time t, including confidential and private information.

The words ‘weak’, ‘semi-strong’ and ‘strong’ indicate that if a stronger form of the efficient market hypothesis is true, a weaker form is true as well. For instance, if the strong-form hypothesis is true, the semi-strong and the weak-form hypotheses are true too. As a consequence of the law of iterated expectations, and taking into account (3.2) as well as assuming that (3.2) and $\mathcal{F}_t' \subseteq \mathcal{F}_t$, the following holds:

$$E(R_t - R_t^*|\mathcal{F}_t') = 0. \tag{3.3}$$

What is more, taking into account that (the law of iterated variances):

$$var(r_{t+j}) = E\left(var(r_{t+j}|\mathcal{F}_t)\right) + var\left(E(r_{t+j}|\mathcal{F}_t)\right), \tag{3.4}$$

the following holds:

$$var(r_{t+j}|\mathcal{F}'_t) \geq var(r_{t+j}|\mathcal{F}_t), \tag{3.5}$$

which means that the conditional variance can be reduced by increasing the information set. (3.4) comes from the so-called law of total variance, also called the variance decomposition formula, conditional variance formula, the law of iterated variances, or Eve's law. It states that when the variance of Y is finite and the random variables X and Y come from the same probability space, then:

$$Var(Y) = E(Var(Y|X)) + Var(E(Y|X)). \tag{3.6}$$

where the first component $E(Var(Y|X))$ refers to the unexplained variance (the fraction of variance unexplained or the expected value of the process variance) and the second component $Var(E(Y|X))$ refers to the explained variance (explained variation or the variance of the hypothetical means). Nevertheless, the forecasts become more variable due to the increase of the information set:

$$var(E(r_{t+j}|\mathcal{F}'_t)) \leq var(E(r_{t+j}|\mathcal{F}_t)). \tag{3.7}$$

According to Campbell, Lo and MacKinlay (1997) the aforementioned law of iterated expectations constitutes an explanation for some confusions caused by the idea stating that the efficient security should be random, like the belief that if the prices are determined by discounting future cashflows, the returns cannot be random. The law of iterated expectations, also known as the law of total expectations, the tower rule, Adam's law or the smoothing theorem, states that when the random variable Y is from the same probability space as the random variable X with a defined expected value $E(X)$, then the expected value of the conditional expected value of X conditional on Y is the same as the expected value of X:

$$E(X) = E(E(X|Y)). \tag{3.8}$$

There is also a special case that states that when $\{A_i\}_i$ is a finite or countable partition of the sample space, then:

$$E(X) = \sum_i E(X|A_i)P(A_i). \tag{3.9}$$

Assuming that there are two information sets, i.e., I_t, and J_t, where $I_t \subseteq J_t$ (the information set J_t comprises all information of I_t plus some extra information), the expected values of the random variable X conditional on the information sets I_t, and J_t, are considered:

$$E(X|I_t) \ or \ E(X|J_t). \tag{3.10}$$

Taking into account the law of iterated expectations:

$$E(X|I_t) = E(E(X|J_t)|I_t) \tag{3.11}$$

the following holds:

$$E(X - E(X|J_t)|I_t) = 0. \tag{3.12}$$

(3.12) indicates that with the use of the limited information set I_t the best forecast of the random variable X which can be made is the forecast of the forecast of the random variable X that can be made with the use of the broader information set J_t. Moreover, a limited information set I_t cannot be used for predicting the forecast error, which could be made with the use of the broader information set J_t.

Assuming that the asset price P_t constitutes a rational expectation of a fundamental value V^*, conditional on information set I_t, which is available at time t, the asset price P_t can be formulated as follows:

$$P_t = E(V^*|I_t) = E_t V^*, \tag{3.13}$$

and in the next period:

$$P_{t+1} = E(V^*|I_{t+1}) = E_{t+1} V^*, \tag{3.14}$$

thus, taking into account that $I_t \subseteq I_{t+1}$, and the law of iterated expectations saying that:

$$E_t(V^*) = E_t(E_{t+1}(V^*)), \tag{3.15}$$

the expected price change over the next period can be formulated as follows:

$$E_t(P_{t+1} - P_t) = E_t\big(E_{t+1}(V^*) - E_t(V^*)\big) = 0. \tag{3.16}$$

Due to (3.16), given the information set I_t, the realized price changes cannot be forecasted.

For Linton (2019) the formulation of the efficient market hypothesis is vague due to many undefined terms. For example, the efficient market hypotheses state that the information (depending on the information set considered) is fully reflected in prices. According to Linton, the term ‘fully reflected’ is usually understood as ‘instantly reflected’, which in practice is a fiction. The researcher proposes that the choice of the reasonable timeframe corresponding to the essence of the theory is an individual matter. The vagueness also concerns the information set. The theory does not precise which historical prices should be considered, for instance, closing, opening, hourly, weakly prices, etc.

The reaction of prices to new information constitutes a willingly undertaken issue in the academic literature. Many issue-related studies indicated the occurrence of anomalies in the context of the informational efficiency, such as the overreaction, underreaction, post-event continuation of pre-event abnormal returns, or post-event reversals. Examples of such anomalies are visualised in Figure 3.2. Despite many studies proving the occurrence of the market efficiency anomalies, Fama (1998) proposes that the market efficiency hypothesis holds even in the face of challenges from the studies on the long-term return anomalies. According to Fama, the anomalies are in line with the market efficiency hypothesis as they are a results of a small chance. As an argument for the market efficiency hypothesis, the overreaction is about as common as the underreaction, and the post-event continuation of the event abnormal returns is about as common as post-event reversal. Fama also proposed that the observed anomalies are mostly caused by the methodology, which does not indicate any anomalies when it is reasonably adjusted.

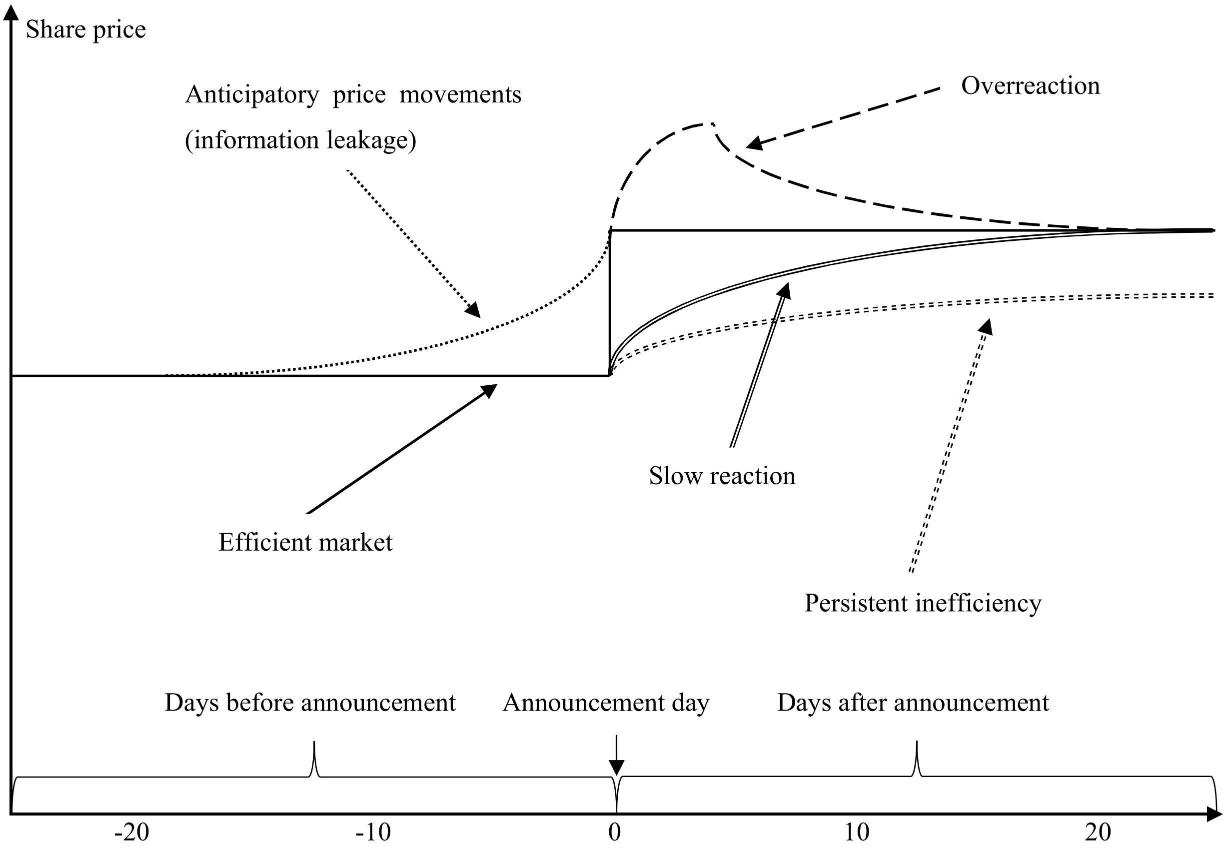

Fig. 3.2. The reaction of stock prices to a new information in the efficient and inefficient market. Source: Author's own study based on Fama (1998)

3.3.The random walk model

According to the efficient market hypothesis, the expected price of financial asset can be described by the following formula (Osińska, 2006):

$$E(P_{t+1}) = P_t(1+r) + \beta_1 E(d_{t+1}) + \beta_2 E(X_{t+1}) + \beta_3 E(e_{t+1}), \quad (3.17)$$

where:
P_t – the price of financial asset at time t,
r – interest rate referring to the cost of opportunity to possess financial assets which can generate a market risk premium,
β_1 – a positive constant that determines the influence of a future dividend on the price of the asset,

β_2 – a positive constant that defines the influence of external publicly available information that is not included in historical asset prices on the asset price,
β_3 – a positive constant that refers to the influence of confidential and private information on the price of the asset,
d_{t+1} – a future dividend paid at time $t+1$,
X_{t+1} – forecastable (publicly available information) and known to the researcher factors, which can influence the future asset price,
e_{t+1} – factors unknow to the researcher, which can be known to some other market participants (confidential and private information), which can influence the future asset price.

The above-mentioned cause and effect equation that defines the expected price of financial asset indicates the sources of the forecasting premises of investors, i.e., proposes factors that describe price expectations of the market participants. The formula distinguishes different sources of information that can be possessed by the market participants. The set of information they possess can include both all publicly available information and the confidential and private information. Thus, the levels of market efficiency are relativized depending on the information set possessed. Due to the dividend included in (3.17), the equation can be used mainly for stock prices. To apply the equation to other assets, it should be modified and include other variables that have an impact on the asset value.

The expected future return can be described with the following equation:

$$E(R_{t+1}) = \frac{E(P_{t+1}) - P_t}{P_t}. \tag{3.18}$$

On the informationally efficient markets it is not possible to gain abnormal returns. However, if one earns abnormal profits, they are accidental. Thus:

$$E(R_{t+1}) = r. \tag{3.19}$$

Taking into account (3.19) and solving (3.18) for P_t, the formula as follows is received:

$$P_t = \frac{E(P_{t+1})}{1+r}. \tag{3.20}$$

For short periods and low interest rates, it is assumed that $r = 0$. (3.20) is true only, if in (3.17):

$$\beta_1 = \beta_2 = 0, \tag{3.21}$$
$$\beta_3 = 0 \; or \; E(e_{t+1}) = 0. \tag{3.22}$$

If the market is informationally efficient in a weak form, then:

$$E(P_{t+1}) = P_t, \tag{3.23}$$

The following results from the above-mentioned considerations:

$$P_{t+1} = P_t + e_{t+1}, \tag{3.24}$$

(3.24) is a random walk when the expected value and the variance of e_{t+1} for a given P_t cannot be forecasted, i.e.,

$$E(e_{t+1}|P_t) = 0, var(e_{t+1}|P_t) = const. \tag{3.25}$$

When the average cannot be forecasted and the variance or any other moment of the distribution is forecastable, (3.24) is a martingale that reflects a process that describes a fair market game, whose expected value equals zero. A martingale constitutes a basis for the weak-form efficiency hypothesis which is approved nowadays (Osińska, 2006).

Usually, the weak-form efficiency hypothesis is the object of the statistical verification as this form of the efficient market hypothesis has the most direct relation with the random walk model. The empirical testing of the weak form of the EMH consists in verifying if the financial asset time series are subject to the random walk process. (3.26) is the random walk process of the price of the investment fund participation unit if the distribution of the random component ε_t meets some specific assumptions discussed in the following part of this chapter (Zamojska, 2012):

$$y_t = y_{t-1} + \varepsilon_t \tag{3.26}$$

3.4. Assumptions about the innovations of returns

One of the most often cited classifications of random walk hypotheses was proposed by Campbell, Lo, and MacKinlay (1997). The researchers distinguished 3 types of random walk, where each next type is weaker. The identification of the random walk process type has a significant meaning, for instance, when it comes to the construction of the returns model and the evaluation of its utility for the forecasting of future returns. Random walk types distinguished by Campbell, Lo and MacKinlay (1997) have the following assumptions:

1) random walk of the first type (RW1) constitutes a process in which the increments ε_t of the process are independent and have identical distributions with the expected value of 0 and the same variance, i.e., $\varepsilon \sim i.i.d.(0, \sigma^2)$,
2) random walk of the second type (RW2) constitutes a process in which the increments ε_t of the process are still independent but may have different distributions. In this type of random walk, heteroscedasticity occurrence is possible,
3) random walk of the third type (RW3) constitutes a process in which the increments ε_t constitute an uncorrelated process. Thus, some dependencies of higher rank moments are possible.

Table 3.1. organizes various versions of random walk and martingale hypotheses proposed by Campbell, Lo, and MacKinlay (1997). A key of the systematization of hypotheses in Table 3.1. is a consideration of various types of dependence between the asset returns r_t and r_{t+k} at time t and $t + k$. Functions $f(r_t)$ and $g(r_{t+k})$ presented in Table 3.1. refer to random

variables. Functions $f(\cdot)$ and g(·) refer to arbitrary functions. Table 3.1. considers a situation in which:

$$Cov[f(r_t), g(r_{t+k})] = 0 \tag{3.27}$$

for all t and for $k \neq 0$. (3.27) virtually captures all versions of random walk and martingale hypotheses proposed by Campbell, Lo, and MacKinlay (1997), depending on the chosen arbitrary functions $f(\cdot)$ and g(·), restricting them to be arbitrary linear functions or not.

$Cov[f(r_t), g(r_{t+k})] = 0$, for all t and for $k \neq 0$	$g(r_{t+k})$, for all g(·)	$g(r_{t+k})$, for all linear g(·)
$f(r_t)$, for all $f(\cdot)$	Independent increments, Random Walk 1 (RW1) and 2 (RW2): $pdf(r_{t+k}\mid r_t) = pdf(r_{t+k})$, where: $pdf()$ – probability density function	Martingale: $E(r_{t+k}\mid r_t) = \mu$
$f(r_t)$, for all linear $f(\cdot)$	–	Uncorrelated increments, Random Walk 3 (RW3): $Proj[r_{t+k}\mid r_t] = \mu$, where: $Proj[r_{t+k}\mid r_t]$ – linear projection of r_{t+k} onto r_t.

Tab. 3.1. Classification of random walk and martingale hypotheses. Source: Author's own study based on Campbell, Lo, and MacKinlay (1997)

If (3.27) holds for:

- all functions $f(\cdot)$ and g(·), then the returns are mutually independent, corresponding to random walk 1 (RW1) and random walk 2 (RW2) models,
- functions $f(\cdot)$ and g(·) which are restricted to be arbitrary linear functions, then the returns are serially uncorrelated, corresponding to random walk 3 (RW3),

- function $f(\cdot)$ which is unrestricted to be an arbitrary linear function and function g(·) which is restricted to be an arbitrary linear function, then (3.27) is equivalent to martingale hypothesis.

According to the random walk hypothesis, future prices cannot be forecasted with the use of historical ones due to their completely random changes. Nevertheless, the assumptions of the random walk model turned out to be too strict and not compatible with the empirical financial time series. This situation suggests that the application of approach that uses the martingale feature seems to be more appropriate for the analysis of the forecasting features of financial time series (Zamojska, 2012). The martingale model is one of the earlies models of financial asset prices whose origins reach the birth of probability theory and the origins of chance games. Already in 1565, in a manuscript 'Liber de Ludo Aleae' ('The Book of Games of Chance'), a prominent Italian mathematician Girolamo Cardano proposed an elementary theory of gambling. The author emphasised that equal conditions are the most fundamental principle of all in gambling, i.e., he proposed that gambling has to be a fair game. A fair game, namely, a game in which none of the opponents is privileged, is the essence of a martingale. Martingale is a stochastic process that satisfies the following condition:

$$E[p_{t+1}|p_t, p_{t-1}, \dots] = p_t, \tag{3.28}$$

or, the equivalent condition as follows:

$$E[p_{t+1} - p_t|p_t, p_{t-1}, \dots] = 0. \tag{3.29}$$

Taking into account (3.28) and assuming that p_t refers to the cumulative winnings or wealth of a player at time t, when the game of chance is a fair game, the expected wealth in the next period $t + 1$ is equal to the wealth in period t. Referring to the equivalent condition (3.29), the expected incremental winnings in a fair game, at any stage of the game of chance, equal zero when conditioned on the history of the game of chance.

Referring the martingale hypothesis to the prices of financial assets, and taking into account (3.28), when p_t is assumed to be the price of financial asset at time t, the price at time $t + 1$ is expected to be the same, given the entire history of asset prices. Referring to the equivalent condition (3.29), when conditioned on the historical asset prices, the expected change in the asset price equals zero. In other words, the probability of the rise and fall of the asset price is the same. According to the martingale hypothesis in the forecasting context, a price today is the best forecast of a price tomorrow due to a minimal mean-squared error. With the use of the martingale time series of the financial asset prices, it is not possible to forecast the future prices on the basis of the historical ones. The conditional expectation on the future changes of asset price, conditional on the asset price history, must equal zero, as if the short sales are feasible, the conditional expectations cannot be either negative or positive. The more random the sequence of the asset price changes generated by the market, the more efficient the market (Campbell, Lo, & MacKinlay, 1997).

The martingale process describes conditional expectations related to asset prices. At the same time, the martingale process does not place restrictions on the constancy of variance. In the martingale model, the heteroscedasticity and dependence may occur at the higher rank moments. Nevertheless, the increments in the martingale model are still uncorrelated. The martingale model also allows verification of prognostic features of financial asset returns. If the logarithms of the asset prices are the martingale defined as follows:

$$\ln p_t = \mu + \ln p_{t-1} + \varepsilon_t, \tag{3.30}$$

then, after modification of this formula by moving the logarithm of the asset price from the previous period p_{t-1} to the left side of the equation, a martingale difference series (MDS) is received (Zamojska, 2012):

$$\ln p_t - \ln p_{t-1} = \mu + \varepsilon_t, \tag{3.31}$$

$$r_t = \mu + \varepsilon_t, \tag{3.32}$$

where:
r_t – the increment of the logarithm of financial asset price.

As a powerful tool in statistics and probability that have important applications in modern financial theories, the martingale has a long history of being considered a necessary condition which has to be fulfilled in order to call the market informationally efficient in a weak form. Nevertheless, some studies proposed that despite the intuitive appeal which the interpretation of a fair game may have, the martingale property is neither a sufficient nor necessary condition to consider the asset prices rationally determined. For instance, the martingale hypothesis places a restriction on expected returns only, without accounting for risk. Due to one of the central modern financial tenets, there is a necessity of making a trade-off between the expected return and risk. Hence, the expected positive price change of asset may be a reward necessary to attract investors to hold the risky asset and bear the risk associated with this asset. However, the martingale property holds when the returns of asset are properly adjusted for risk (Campbell, Lo, & MacKinlay, 1997).

As opposed to Campbell, Lo, and MacKinlay (1997), Linton (2019) has distinguished five different assumptions pertaining to the innovation process for the purpose of testing applications, where the first and second assumption (rw1 and rw2) of Linton (2019) refers to the first and second assumption (RW1 and RW2) of Campbell, Lo, and MacKinlay (1997). However, RW3 of Campbell, Lo, and MacKinlay (1997) refers to rw5 of Linton (2019):

1) rw1 - ε_t are i.i.d. with $E(\varepsilon_t) = 0$,
2) rw2 - ε_t are independent over time with $E(\varepsilon_t) = 0$,
3) rw3 - ε_t constitute a martingale difference sequence, in the sense that for each t, the expected value of ε_t is $E(\varepsilon_t|\varepsilon_{t-1}, \varepsilon_{t-2}, \dots) = 0$, with probability one,
4) rw4 - ε_t for all t and k has $E(\varepsilon_t|\varepsilon_{t-k}) = 0$, with probability one,
5) rw5 - ε_t for all t and k has $E(\varepsilon_t) = 0$, and $cov(\varepsilon_t|\varepsilon_{t-k}) = 0$.

For a clear distinction of the random walk hypotheses, hereinafter the random walk hypotheses proposed by Campbell, Lo, and MacKinlay (1997) will be written with capital letters (RW) and the random walk hypotheses proposed by Linton (2019) will be in lowercase (rw).

3.5. Weak-form efficient market hypothesis testing

Campbell, Lo, and MacKinlay (1997) proposed a broad range of the most commonly applied tests for each of 3 random walk types they distinguished. Pointing out that RW1 (increments ε_t of the process are independent and have identical distributions) is implausible for the time series of financial asset, the researchers enumerated such tests for RW1 as sequences and reversals test and runs test. RW2 assumes that the increments ε_t of the process are still independent but may have different distributions. RW2 constitutes a weaker form of the random walk than RW1. RW2 has been formulated in response to the implausibility of holding the restriction of identical distributions, especially when considering very long time series of financial data. Nevertheless, making no assumptions about the identity of distributions while testing for independence can be troublesome. Conducting statistical inference becomes almost impossible when no restrictions pertaining to the variation of the marginal distributions through time are placed, since it is infeasible to derive the sampling distribution of even the most elementary statistics. Campbell, Lo, and MacKinlay (1997) enumerate two types of test of RW2, i.e., filter rules and technical analysis. For practical reasons, the aforementioned tests have caught a lot of attention from the academic and professional community, although none of them have made much use of formal statistical inference. RW3 is the weakest form of random walk and constitutes a process in which the increments ε_t of the process are uncorrelated. Under this type of random walk, the increments or first differences are uncorrelated at all leads and lags. Thus, RW3 can be tested by verifying the null hypothesis which states that the autocorrelation coefficients of the first differences at various lags are equal to zero. Because of the above-mentioned, checking for serial correlation, i.e., correlation between two observations from the same time series at different dates, is one of the most direct and intuitive tests of random walk and martingale hypothesis for individual time series. In order to test the RW3 and martingale hypotheses, Campbell, Lo, and MacKinlay (1997) proposed some appropriately adjusted tests based on variance ratios.

Despite the incompatibility of features of financial time series with the assumptions of RW1, the majority of studies dedicated to efficient market hypothesis testing apply tests under RW1, as RW1 requires application of the simplest test statistics. The weaker the hypothesis, the more complicated the test statistics. According to the law of decreasing credibility, stating that the stronger the assumptions, the less credible the inference, it is better to consider weaker, but more difficult to test assumptions about the random walk (Linton, 2019). Czekaj (2014) emphasizes that one should be particularly careful when drawing conclusions from the tests under RW1 such as the autocorrelation test. The autocorrelation test has been designed under the assumption of linearity and normality of the analysed returns. Due to the nonlinearity and fat tails of the analysed time series of returns, which are subject to power law of scaling, the autocorrelation (ACF) and partial autocorrelation functions (PACF) feature nonstandard statistical features, which make it impossible to apply classic econometric tests and procedures. In the study on the informational efficiency of the stock market in Poland, Czekaj (2014) emphasized that the autocorrelation function was applied only for a qualitative evaluation of the information transmission and liquidity of the market.

Nevertheless, due to a common application of tests under RW1, their simplicity, and the basis which they constitute for tests under more general conditions than RW1, the tests under RW1 will be discussed in the subsequent part of this chapter.

Before the presentation of the random walk tests, the concepts of stationary and stationary testing will be discussed. A class of the unit root tests, i.e., stationarity tests, commonly appears in academic studies dedicated to the random walk testing. However, the unit root tests are often confused with the tests of the random walk hypotheses. They are not designed to detect predictability in time series, but only to test whether the time series are stationary or not, as the non-stationarity is just one of the features of the random walk process (Campbell, Lo, & MacKinlay, 1997). Bearing in mind a discrete time stochastic process X_t for $t = 1, 2, 3, \ldots$, which constitutes the random walk model that captures the notion of the absence of predictability:

$$X_t = X_{t-1} + \varepsilon_t \tag{3.33}$$

or the random walk model with a drift term μ:

$$X_t = \mu + X_{t-1} + \varepsilon_t \tag{3.34}$$

the process X_t is non-stationary under rw1. However, the innovation process ε_t is stationary. Under rw3 (a martingale hypothesis), the innovation process ε_t (a martingale difference sequence) does not have to be stationary (Linton, 2019).

3.5.1. The analysis of stationarity

The stationarity of financial time series plays a very important role in the development of asset pricing models. The description of features of data-generating process is one of the main goals of the asset pricing model development. The development of asset pricing models is based on some assumptions that allow researchers to create some theoretical patterns in regard of which some evaluations and comparisons will be possible. Stationarity and ergodicity are one of the basic assumptions made for variables which appear in asset pricing models (Zamojska, 2012). Asset pricing models estimated on the basis of the nonstationary time series do not have desirable statistical features. Moreover, the non-stationarity of financial time series may lead to wrong conclusions drawn on their basis. The estimation of models based on nonstationary time series may cause that the standard statistics used to evaluate the quality of the model may be affected by errors. It may lead to the approval of the apparent dependence.

Also, the estimators of stochastic parameters may be invalid. The apparent regression which is a consequence of application of regression analysis to nonstationary time series, leads to:

- the overestimation of determination coefficient,
- the overestimation of Student's t-statistic and biasing other statistics.

The non-stationarity of time series can be caused by:

- the non-existing moments of stochastic process,
- the varying variance of time series,
- the presence of deterministic trend in the average.

A stochastic process can be stationary in a narrow sense, i.e., it can be strongly stationary, or it can be stationary in a broad sense, i.e., it can be weakly stationary. From a practical point of view, it is sufficient when the stochastic process is stationary in a broad sense.

A stationary process has a constant variance, and the values of variances in particular moments vary around a certain level. This level constitutes an average level over the entire research period. A stationary process can be stabilised at a new level in the case of more rapid changes (Witkowska, Matuszewska-Janica, & Kompa, 2012).

Another assumption made for variables that appear in the asset pricing models is the ergodicity. Ergodicity ensures, particularly, the convergence of the empirical moments of distribution to a true expected value and variance. Ergodicity is a feature of all random variables with i.i.d. distribution. Due to ergodicity, the estimation of the probability distribution of the process and its parameters is possible on the basis of the single realisation of process, i.e., observed time series over a sufficiently long period.

If the joint and conditional distributions of the process do not change along with the movements in time, a stochastic process is strongly stationary (in a narrow sense). In other words, for a given set of moments in time $t_1, \ldots, t_k$ and any interval Δt, the joint distribution of probability of returns:

$$r(t_1, T), \ldots, r(t_k, T),$$

is the same as the joint distribution of probability of returns moved in time by Δt (Czekaj, 2014):

$$r(t_1 + \Delta t, T), \ldots, r(t_k + \Delta t, T).$$

A stochastic process is stationary within the meaning of the covariance, or is weakly stationary if the value of covariance between the observations from two periods depends just on the interval between these observations, and the two first moments of the joint distribution are finite and constant. Thus, a stochastic process $\{Y_t\}$ is stationary in the broad sense (is weakly stationary) if:

- $E(Y_t) = const,$

- $S^2(Y_t) = const,$
- $cov(Y_t, Y_{t+\Delta t})$ depends only on Δt.

Stationarity is related to the concept of integration. The following levels of integration can be distinguished:

- $y_t \sim I(0)$ – the analysed process is integrated at the zero level when the process is stationary,
- $y_t \sim I(1)$ – the analysed process is integrated at the first level when the process is nonstationary but its first differences are stationary,
- $y_t \sim I(2)$ – the analysed process is integrated at the second level when the process as well as the first differences are nonstationary, but the second differences of the process are stationary,
- $y_t \sim I(d)$ - the analysed process is integrated at level d when its differences are stationary after d-fold differentiation.

The level of integration of random variables should be tested, for instance, in the process of the model development. The estimation of models on the basis of the nonstationary time series may result, for example, in biased standard statistics used for the evaluation of the quality of the model. In addition, it may lead to the approval of the apparent dependence, and invalidity of estimators of stochastic parameters.

The problem of non-stationarity pertains to many economic time series, like the macroeconomic time series, as well as financial time series. In the studies which use financial time series, the most common way of solving the problem of non-stationarity is to calculate logarithmic returns. Most financial time series, such as exchange rates, or stock prices, are integrated at the first level ($y_t \sim I(1)$). Therefore, despite the fact that exchange rates, or share prices are not stationary, their logarithmic returns indeed are. Logarithmic returns can also be considered as differences because the logarithmic return is a difference between the logarithms of prices.

As mentioned before, in most cases of the nonstationary time series, their first differences are already stationary. Nevertheless, a nonstationary process can also be adjusted into a stationary one with the use of an appropriate filter which depends on the type of non-stationarity. The application of the trend function as a filter will be sufficient when the process exhibits stationary deviations around the deterministic trend. The application of the differential trend as a filter will be sufficient when the process has a stochastic trend. Some processes include both types of trends.

In order to verify whether the examined time series are stationary the so-called the unit root tests are used. The class of unit root tests is often confused with the tests of random walk hypotheses. Unit root tests are not designed to detect predictability in time series, but only to test whether time series are stationary or not, as non-stationarity is just one of the features of the random walk process. Nevertheless, unit root tests often appear in studies dedicated to the verification of the efficient market hypothesis.

A basic model used in the unit root tests can be formulated as follows:

$$y_t = \widetilde{\alpha_1} y_{t-1} + \varepsilon_t, \tag{3.35}$$

where:
y_t – observation in the time series in period t,
y_{t-1} – observation in the time series in period $t-1$,
$\widetilde{\alpha_1}$ – the unknown parameter of the model which should be estimated,
ε_t – an error component.

When parameter $\widetilde{\alpha_1}$ equals one ($\widetilde{\alpha_1} = 1$) the above-mentioned model verified by the unit root test describes a random walk model formulated earlier in this chapter:

$$y_t = y_{t-1} + \varepsilon_t. \tag{3.36}$$

The random walk process ($y_t = y_{t-1} + \varepsilon_t$) is nonstationary, as opposed to the time series of its first differences ($y_t - y_{t-1} = \varepsilon_t$). The model which describes the random walk process constitutes a process that contains a unit root as its $\widetilde{\alpha_1}$ parameter statistically does not differ from one. A process is considered to be stationary when the absolute value of $\widetilde{\alpha_1}$ is lower than one ($|\widetilde{\alpha_1}|<1$). The case where the absolute value of $\widetilde{\alpha_1}$ exceeds one ($|\widetilde{\alpha_1}|>1$) is not considered as $\widetilde{\alpha_1}$ that exceeds one may cause that the time series y_t is exploding.

In practice, the test of significance of $\widetilde{\alpha_1}$ is conducted after the rearrangement of (3.35), assuming that:

$$\widetilde{\alpha_1} = 1 + \alpha_1, \tag{3.37}$$

into:

$$y_t = (1 + \alpha_1) y_{t-1} + \varepsilon_t, \tag{3.38}$$

and finally into:

$$\Delta y_t = \alpha_1 y_{t-1} + \varepsilon_t. \tag{3.39}$$

In this case the verification of hypothesis which states that $\alpha_1 = 0$ is conducted, not $\widetilde{\alpha_1} = 1$ as it might seem. When a tested hypothesis is rejected, i.e., when $\alpha_1 < 0$ and $\widetilde{\alpha_1} < 1$, it can be assumed that the analysed time series are stationary.

The stationarity of nonstationary time series is examined after the application of filters in the form of:

- trend function, in the case of trend-stationary time series,
- differentiation, in the case of time series with a stochastic trend (time series with a trend in variance).

Unit root tests can be divided into two groups taking into account the way of formulating hypothesis:

a) tests that verify the existence of the autoregressive unit root. In such tests the null hypothesis and alternative hypothesis are formulated as follows:

$$H_0: y_t \sim I(1); \tag{3.40}$$

$$H_1: y_t \sim I(0). \tag{3.41}$$

Among the most popular tests that verify the hypotheses mentioned above are:

- Dickey-Fuller test (DF),
- Augmented Dickey-Fuller test (ADF),
- Phillips test,
- Phillips-Perron test (PP),
- Sargan-Bhargava test (IDW)

b) tests that verify the existence of unit roots in the moving average, In such tests the null hypothesis and alternative hypothesis are formulated as follows:

$$H_0: y_t \sim I(0); \tag{3.42}$$

$$H_1: y_t \sim I(1). \tag{3.43}$$

Among the most popular tests that verify the hypotheses mentioned above are:

- Kwiatkowski-Philips-Schmidt-Shin test (KPSS),
- Nabey-Tanak test
- Leybourne-McCabe test
- Park test
- Lagrange's multiplier test
- SBDH test
- modified LM and SBDH statistics,
- Breitung test,
- Said-Dickey test.

One of the most frequently used stationarity tests that verify the existence of the autoregressive unit root are the stationarity tests by Dickey and Fuller. Both versions of the test by Dickey and Fuller, namely, the test in the basic (AD) and augmented (ADF) form verify the null hypothesis which states that the examined time series are integrated at the zero level. The basic form of the Dickey-Fuller test begins with the estimation of one of the following equations using the least squares approximation method:

$$\Delta y_t = \alpha_1 y_{t-1} + \varepsilon_t, \tag{3.44}$$

$$\Delta y_t = \alpha_0 + \alpha_1 y_{t-1} + \varepsilon_t, \tag{3.45}$$

$$\Delta y_t = \alpha_0 + \lambda_1 t + \alpha_1 y_{t-1} + \varepsilon_t, \tag{3.46}$$

where:
$\Delta y_t = y_t - y_{t-1}$,
y_t – observation in period t,
y_{t-1} – observation in period $t-1$,
t – time variable,
α_1 – the unknown parameter of model which should be estimated and tested,
α_0 – a constant term,
λ_1 – the parameter of time variable,
ε_t – an error component.

In the case of the occurrence of a constant trend, also known as a drift, the equation (3.45) finds its application. A deterministic trend is taken into account by (3.46).

A basic form of the Dickey-Fuller test does not take into account a frequently appearing feature of time series, namely, the autocorrelation of time series. This feature implicates the autocorrelation of the error component. The augmented Dickey-Fuller test has been proposed in order to account for autocorrelation. The adjustments in Dickey-Fuller test implicated some changes in formulas (3.44), (3.45), and (3.46). The augmented Dickey-Fuller test begins with the estimation of one of the following equations, which constitute the adjusted versions of equations (3.44), (3.45), and (3.46):

$$\Delta y_t = \alpha_1 y_{t-1} + \sum_{i=1}^{p} c_i \Delta y_{t-i} + \varepsilon_t, \tag{3.47}$$

$$\Delta y_t = \alpha_0 + \alpha_1 y_{t-1} + \sum_{i=1}^{p} c_i \Delta y_{t-i} + \varepsilon_t, \tag{3.48}$$

$$\Delta y_t = \alpha_0 + \lambda_1 t + \alpha_1 y_{t-1} + \sum_{i=1}^{p} c_i \Delta y_{t-i} + \varepsilon_t, \tag{3.49}$$

where:
Δy_{t-i} – the value of the first differences in period $t-i$,
c_i – the parameter of the regression line standing by variable Δy_{t-i},
p – the value of the maximum lag of the independent variable.

After the estimation of one of the models from (3.44) to (3.49), the following hypotheses are verified:

$$H_0: \alpha_1 = 0; \tag{3.50}$$
$$H_1: \alpha_1 < 0. \tag{3.51}$$

The null hypothesis is verified with the use of t_{DF} statistic. The formula for t_{DF} statistic is as follows:

$$t_{DF} = \frac{\widehat{\alpha_1}}{S(\widehat{\alpha_1})}, \tag{3.52}$$

where:
$\widehat{\alpha_1}$ – the estimation of α_1 parameter obtained with the use of the least squares approximation method,
$S(\widehat{\alpha_1})$ – a standard estimation error for α_1 parameter.

To verify the null hypothesis, specially calculated critical values are applied due to nonnormality and negative skewness of the distribution of t_{DF} statistic. The time series y_t is stationary, i.e., it is integrated at the zero level ($y_t \sim I(0)$) when the critical value allows for rejection of the null hypothesis. When the time series y_t is not stationary, i.e., there are no grounds for the rejection of the null hypothesis, the test has to be repeated, but this time for the first differences. When the analysed time series does not become stationary after calculating differences of any order, it needs to be verified whether, in such a time series, any stochastic unit roots appear (Witkowska, Matuszewska-Janica, & Kompa, 2012).

The Perron test constitutes a modification of the augmented test by Dickey and Fuller. The modification of the ADF test proposed by Perron takes into account a change in the structure of time series marked by a linear deterministic trend. The change in the structure of trend may refer to:

- a constant term,
- a slope,
- a constant term and a slope.

Depending on the change in trend which is taken into account, in the first step of the Perron test one of the models presented below should be estimated. The equations indicated below constitute the transformations of (3.49) that comes from the ADF test:

$$y_t = \alpha_0 + \lambda_1 t + \lambda_2 D(U)_t + \lambda_3 D(TB)_t + \alpha_1 y_{t-1} + \sum_{i=1}^{p} c_i \Delta y_{t-i} + \varepsilon_t, \tag{3.53}$$

- used when only the change in the constant term is assumed,

$$y_t = \alpha_0 + \lambda_1 t + \lambda_2 D(U)_t + \lambda_4 D(T^*)_t + \alpha_1 y_{t-1} + \sum_{i=1}^{p} c_i \Delta y_{t-i} + \varepsilon_t, \tag{3.54}$$

- used when only the change in slope is assumed,

$$y_t = \alpha_0 + \lambda_1 t + \lambda_2 D(U)_t + \lambda_3 D(T)_t + \lambda_4 D(TB)_t + \alpha_1 y_{t-1} + \sum_{i=1}^{p} c_i \Delta y_{t-i} + \varepsilon_t, \tag{3.55}$$

- Used when the change in both constant term and slope are assumed,

where:
y_t – the value of observation in the time series in period t,
$\alpha_0, \lambda_1, \lambda_2, \lambda_3, \lambda_4, \alpha_1, c_i$ – the structural parameters of the model,
t – a variable that reflects a trend, $t = 1, 2, 3, \dots, T$,

T_B – the moment of the occurrence of the change in the structure of the trend,

$$D(U)_t = \begin{cases} 1, for\ t > T_B \\ 0, for\ t \leq T_B \end{cases},$$
$$D(TB)_t = \begin{cases} 1, for\ t = T_B + 1 \\ 0, for\ t \neq T_B + 1 \end{cases},$$
$$D(T^*)_t = \begin{cases} t - T_B, for\ t > T_B \\ 0, for\ t \leq T_B \end{cases},$$
$$D(T)_t = \begin{cases} t, for\ t > T_B \\ 0, for\ t \leq T_B \end{cases}.$$

(3.53) is used when only the change in the constant term is assumed. The null hypothesis in this case assumes the occurrence of the unit root, i.e., it assumes that the process is not stationary ($\alpha_1 = 1$). In addition, the null hypothesis also assumes the occurrence of a single change, also called a shock. The alternative hypothesis assumes that the process is stationary, i.e., it assumes that the unit root does not occur ($\alpha_1 < 1$). Additionally, it also assumes that the change refers to the change in the constant term, without having a feature of a shock. These hypotheses can also be formulated as follows:

$$H_0: \lambda_1 = 0; \lambda_2 = 0; \lambda_3 \neq 0; \alpha_1 = 1; \quad (3.56)$$
$$H_1: \lambda_1 \neq 0; \lambda_2 \neq 0; \lambda_3 = 0; \alpha_1 < 1. \quad (3.57)$$

Figure 3.3. presents an exemplary change in the constant term (the occurrence of shock) in a linear deterministic trend.

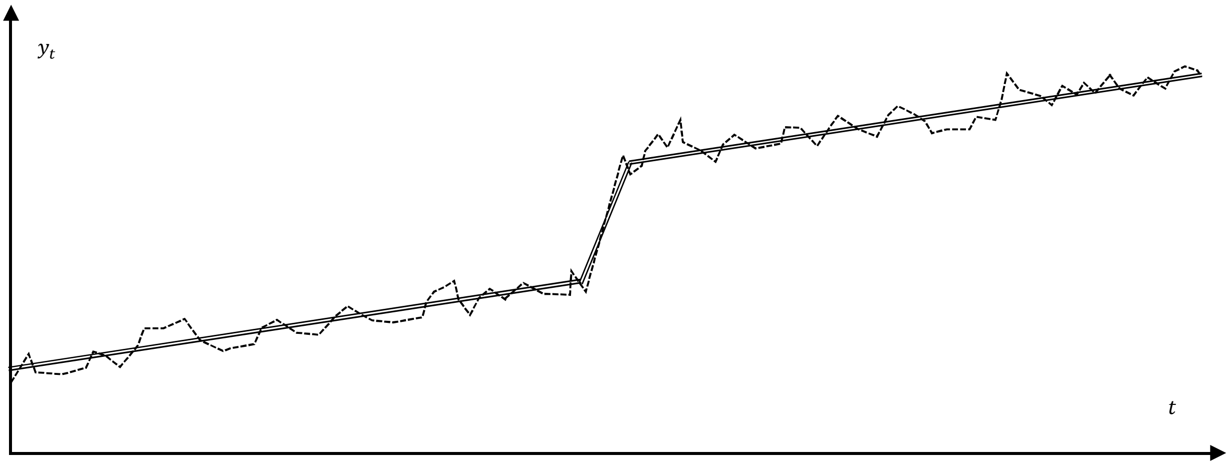

Fig. 3.3. The change in the constant term (occurrence of a shock) in a linear deterministic trend. Source: Author's own study based on Witkowska, Matuszewska-Janica, and Kompa (2012)

(3.54) is used when only the change in slope is assumed. The null hypothesis in this case assumes the occurrence of the unit root, i.e., it assumes that the process is not stationary ($\alpha_1 = 1$). The alternative hypothesis assumes that the process is stationary, i.e., is assumes that the unit root does not occur ($\alpha_1 < 1$). In addition, it assumes that the change in slope is significant. Hypotheses can also be formulated as follows:

$$H_0: \lambda_1 = 0; \lambda_2 \neq 0; \lambda_4 = 0; \alpha_1 = 1; \quad (3.58)$$

$$H_1: \lambda_1 \neq 0; \lambda_2 = 0; \lambda_4 \neq 0; \alpha_1 < 1. \tag{3.59}$$

Figure 3.4. presents an exemplary change in slope in the linear deterministic trend.

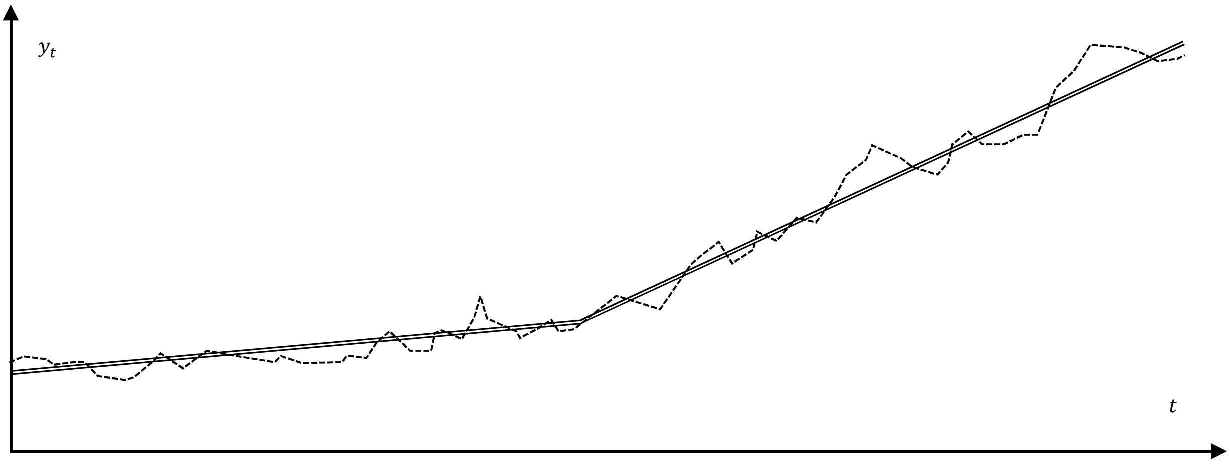

Fig. 3.4. The change in slope in the linear deterministic trend. Source: Author's own study based on Witkowska, Matuszewska-Janica, and Kompa (2012)

(3.55) has to be applied when the changes in both the constant term (the occurrence of shock) and slope in the linear deterministic trend are expected. Hypotheses referring to this test can be formulated in the following way:

$$H_0: \lambda_1 = 0; \lambda_2 = 0; \lambda_3 = 0; \lambda_4 \neq 0; \alpha_1 = 1; \tag{3.60}$$

$$H_1: \lambda_1 \neq 0; \lambda_2 \neq 0; \lambda_3 \neq 0; \lambda_4 = 0; \alpha_1 < 1. \tag{3.61}$$

Figure 3.5. presents an exemplary change in both the constant term (the occurrence of a shock) and slope in the linear deterministic trend.

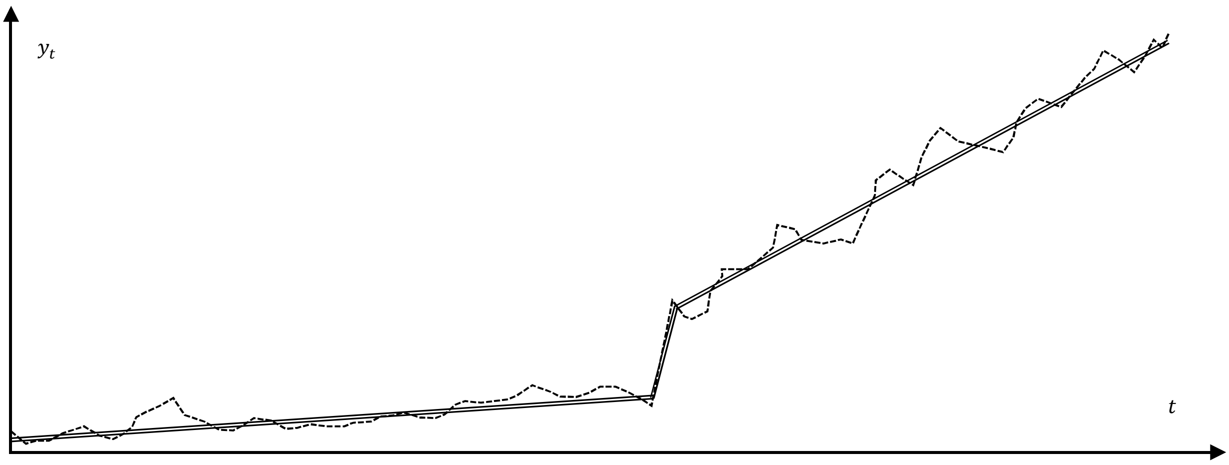

Fig. 3.5. The change in both the constant term (the occurrence of shock) and slope in the linear deterministic trend. Source: Author's own study based on Witkowska, Matuszewska-Janica, and Kompa (2012)

Perron used the t^* statistic for the verification of hypothesis $H_0 = 1$, and proposed new critical values for a particular significance level and the parameter λ, where $\lambda = T_B/T$, as critical values for this test differ from critical values used for the DF and ADF tests. Critical values from the Student's t-distribution are used for the verification of significance of other parameters. A structure change moment is calculated for a variable that reflects the moment of change on the basis of the Student's t-statistic. A point for which the value of statistic is the highest compared to the absolute value has to be taken into account.

3.5.2. Autocorrelation testing

The autocorrelation of time series elements consists in the correlation of observations from different periods but from the same time series. Autocorrelation may result from:

- disturbing factors that affect modelling of the process for more than one measurement period. For instance, measures are made quarterly and the disturbing factors affect the process for half of the year,
- the autocorrelation of interferences that appears with no economic premises,
- specification errors when the ragged variables are missed or incorrectly defined.

The autocorrelation coefficient can be considered as a natural time series extension of the correlation coefficient between two random variables x and y which can be defined with the formula as follows:

$$Corr[x,y] = \frac{Cov[x,y]}{\sqrt{Var[x]}\sqrt{Var[y]}}, \tag{3.62}$$

Given a covariance-stationary time series y, in order to examine autocorrelation, the autocorrelation coefficient ρ_k of order k is estimated as follows:

$$\widehat{\rho_k} = \frac{\sum_{t=k}^{T}(y_t - \bar{y})(y_{t-k} - \bar{y})}{\sum_{t=k}^{T}(y_t - \bar{y})}, \tag{3.63}$$

where:
$\widehat{\rho_k}$ – the autocorrelation coefficient of order k,
y_t – logarithmic return in period t,
y_{t-k} – logarithmic return in period $t-k$,
$\bar{y}$ – the average logarithmic return in the research period,
T – the number of observations in the examined time series,
k – the order of autocorrelation.

The series of autocorrelation coefficients $\widehat{\rho_k}$ for consecutive orders $k = 1, 2, 3, \dots, T - 1$, creates an autocorrelation function (ACF). If the autocorrelation coefficient is calculated for the lag k, i.e., between observations from period y_t and y_{t-k}, the relationship between these observations is disturbed with the information carried by observations from y_{t-1} to y_{t-k+1}. Due to this weakness of autocorrelation coefficient, in statistical analysis, researchers also use a partial autocorrelation coefficient ϕ_{kk} which is free from drawbacks of autocorrelation coefficient $\widehat{\rho_k}$. Partial autocorrelation coefficient ϕ_{kk} eliminates the impact of observations from y_{t-1} to y_{t-k+1} on the autocorrelation coefficient, calculated for the lag k. Partial autocorrelation coefficient ϕ_{kk} can be formulated with the following equation:

$$\phi_{11} = \widehat{\rho_1}, \tag{3.64}$$

$$\phi_{kk} = \frac{\widehat{\rho_k} - \sum_{j=1}^{k-1} \phi_{k-1,j}\, \widehat{\rho_{k-j}}}{1 - \sum_{j=1}^{k-1} \phi_{k-1,j}\, \widehat{\rho_j}}. \tag{3.65}$$

The series of the partial autocorrelation coefficients ϕ_{kk} for consecutive orders $k = 1, 2, 3, \dots, T-1$, creates a partial autocorrelation function (PACF).

Once the autocorrelation coefficients are calculated, in order to find whether they are statistically significant a proper statistical test needs to be conducted. Although there are many different tests that detect statistical significance of the autocorrelation coefficients, in most cases the null hypothesis states that the autocorrelation coefficient equals zero (statistically it is indistinguishable from zero). The alternative hypothesis states that the autocorrelation occurs and is statistically distinguishable from zero. The aforementioned hypotheses can be formulated as follows:

$$H_0 : p_k = 0, \tag{3.66}$$

$$H_1 : p_k \neq 0. \tag{3.67}$$

The Durbin-Watson test and The Durbin-h test are among the most popular tests that allow to detect the first order autocorrelation. Among the most popular tests used for the detection of autocorrelation of any order, are: autocorrelation coefficient test, Breush-Godfrey LM test, test based on the Pearson correlation coefficient test, tests based on the Box-Pierce and Ljung-Box statistic.

One of the tests that can be used to verify the hypothesis about the occurrence of autocorrelation of any order is Pearson's correlation coefficient test. Pearson's correlation coefficient test can be formulated with the following equation:

$$t = \frac{\widehat{\rho_k}}{\sqrt{\frac{1-\widehat{\rho_k}^2}{T-k-2}}}. \tag{3.68}$$

The t statistic of Pearson's correlation coefficient test has Student's t-distribution with $\nu = T - k - 2$ degrees of freedom. If the absolute value of the t statistic is higher than critical value t_α, i.e., $|t| > t_\alpha$, the null hypothesis has to be rejected for the benefit of the alternative one, which means that in the time series there is a statistically significant autocorrelation of order k. It suggests that the examined time series are not subject to the random walk process. A critical value t_α comes from the table of critical values of Student's t-distribution for a given significance level α and ν degrees of freedom.

In the case of the autocorrelation coefficient test, a critical value u_α comes from the table of the cumulative distribution function of the standardized normal distribution, for a given significance level α. If the absolute value of the ω_k statistic is higher than critical value u_α, i.e., if $|\omega_k| > u_\alpha$, the null hypothesis has to be rejected for the benefit of the alternative one, which means that in the time series there is a statistically significant autocorrelation of order k. It suggests that the examined time series is not subject to the random walk process. The ω_k statistic can be formulated as follows:

$$\omega_k = \sqrt{T}\rho_k. \tag{3.69}$$

In contrast to the above-mentioned tests of the autocorrelation coefficient which consider only one autocorrelation coefficient at once, the Box-Pierce Q-statistic considers the sum of a given number of consecutive autocorrelation coefficients. The Box-Pierce Q-statistic comes from the group of portmanteau statistics. Moreover, the Box-Pierce Q-statistic by summing the squared autocorrelations is designed to detect deviations from zero autocorrelations in any direction and at all lags. Nevertheless, attention is required when selecting a number of autocorrelations that need be tested. Too small number of examined autocorrelations may lead to the omission of the presence of higher-order autocorrelations. Too large number of examined autocorrelations may lead to a low power of test due to insignificant higher-order autocorrelations. Since RW1 implies that all autocorrelations equal zero, the Box-Pierce Q-statistic is a simple test statistic of RW1. The formula of the Box-Pierce Q-statistic, also called a joint autocorrelation, is as follows:

$$Q = T\sum_{i=1}^{k}\widehat{\rho_i}^2. \tag{3.70}$$

The Box-Pierce Q-statistic has a χ^2 distribution with k degrees of freedom. When the value of the Box-Pierce Q-statistic exceeds a critical value resulting from the χ^2 distribution for v degrees of freedom and for a given significance level α, i.e., when $Q > \chi^2_{\alpha,v}$, the null hypothesis has to be rejected for the benefit of the alternative one, which means that in the time series there is a statistically significant autocorrelation of order k. It suggests that the examined time series is not subject to the random walk process.

The Box-Pierce Q-statistic was modified by Ljung and Box who proposed a finite-sample correction that yields a better fit to the χ^2 distribution for small sample sizes. The Q^*-statistic of Ljung and Box has a χ^2 distribution with k degrees of freedom and is formulated as follows:

$$Q^* = T(T+2)\sum_{i=1}^{k}\frac{\widehat{\rho_i}^2}{T-i}. \tag{3.71}$$

The same as in the case of the basic version of the Q-statistic by Box and Pierce, when the value of the Q^*-statistic by Ljung and Box exceeds a critical value resulting from the χ^2 distribution for v degrees of freedom and for a given significance level α, i.e., when $Q^* > \chi^2_{\alpha,v}$, the null hypothesis has to be rejected for the benefit of the alternative one, which means that in the time series there is a statistically significant autocorrelation of order k. Again, it suggests that the examined time series is not subject to the random walk process (Witkowska, Matuszewska-Janica, & Kompa, 2012).

3.5.3. Variance ratio tests

Variance ratio tests are based on the important property that features all three random walk hypotheses distinguished by Campbell, Lo, and MacKinlay (1997). According to this property, the variance of the random walk increments must be a linear function of the time interval. Due to the variances of increments, which may vary over time, in the case of the RW2 and RW3 the linearity property may be more difficult to state. Nevertheless, even in such cases the variance of the sum must equal the sum of variances. The variance ratio tests exploit this linearity property. The variance ratio tests are also closely related to the concept of autocorrelation and the Box-Pierce test.

The variance ratio tests were first introduced to finance in the 1980s by Poterba and Summers (1988), and Lo and MacKinlay (1988). Taking into account that for log prices $logP_t$ the continuously compounded returns $r_t = logP_t - logP_{t-1}$ are i.i.d. under RW1, the variance of $r_t + r_{t-1}$ must qual twice the variance of r_t. Therefore, the comparison of variance of $r_t + r_{t-1}$ with twice the variance of r_t can be considered a random walk test. In order to consider the time series of the log returns compatible with the random walk, the aforementioned ratio should be statistically indistinguishable from 1.

Assuming the stationarity of returns, in the variance ratio $VR(2)$, the variance of a two-period log return $r_t(2) = r_t + r_{t-1}$ has to equal twice the variance of a one-period return r_t:

$$\begin{aligned} VR(2) = \frac{Var[r_t(2)]}{2Var[r_t]} = \frac{Var[r_t + r_{t-1}]}{2Var[r_t]} = \frac{2Var[r_t] + 2Cov[r_t, r_{t-1}]}{2Var[r_t]} \\ = 1 + 2\rho(1), \end{aligned} \tag{3.72}$$

where:
$\rho(1)$ – the first-order autocorrelation coefficient of returns r_t.

For any stationary time series and especially under RW1, when all autocorrelations equal zero, the expected value of the variance ratio is one, as the value of the variance ratio $VR(2)$ is one plus the autocorrelation coefficient of the first order. Variances grow faster than linearly when the first-order autocorrelation is positive ($VR(2) > 1$), as the variance of the sum of two one-period returns is larger than the sum of two one-period variances of returns. Alternatively, variances grow slower than linearly when the first-order autocorrelation is negative ($VR(2) < 1$), as the variance of the sum of two one-period returns is smaller than the sum of two one-period variances of returns. To calculate the variance ratio for more periods, higher-order autocorrelations need to be engaged (Campbell, Lo, & MacKinlay, 1997). The following formula presents a generalized variance ratio VR_k for k number of periods:

$$VR_k = \frac{S^2(y_t + y_{t-1} + \cdots + y_{t-k+1})}{kS^2(y_t)}, \tag{3.73}$$

where:
y_t – observation (return) in period t,
$S^2(y_t)$ – variance in the time series of returns y_t,
$S^2(y_t + y_{t-1} + \cdots + y_{t-k+1})$ – variance of the sum of returns $y_t + y_{t-1} + \cdots + y_{t-k+1}$,

The variance ratio VR_k for k number of periods can be also formulated with the following equation:

$$VR_k = \frac{S^2[r_t(k)]}{kS^2[r_t]} = 1 + 2\sum_{i=1}^{k-1}(1 - \frac{i}{k})\hat{p_i} \tag{3.74}$$

where:
$r_t(k) = r_t + r_{t-1} + \cdots + r_{t-k+1}$,
$\hat{p_i}$ – the autocorrelation coefficient of order i,

According to (3.74), the variance ratio VR_k for k number of periods is a particular linear combination of the first $k-1$ autocorrelation coefficients of $\{r_t\}$, with linearly decreasing weights. VR_k equals one under RW1, as $\hat{p_i} = 0$ for all $i > 1$. The same applies to RW2 and RW3, where VR_k must still equal one as the variances of $\{r_t\}$ are finite and the average variance $\sum_{t=1}^{T} S^2[r_t]/T$ converges to a number that is finite and positive (Campbell, Lo, & MacKinlay, 1997).

A standardized variance ratio SVR_k, which allows to verify the null hypothesis stating that the time series is subject to random walk under RW1, is directly used for a statistical inference. It can be applied to large samples and allows for conducting a significance test. The standardized variance ratio SVR_k, which is a normalized statistic of the variance ratio VR_k, can be presented with the following equation:

$$SVR_k = \sqrt{T}(VR_k - 1)\left(\frac{2(2k-1)(k-1)}{3k}\right)^{-\frac{1}{2}}. \tag{3.75}$$

The value of the standardized variance ratio SVR_k is compared to a critical value coming from the tables of a standardized normal distribution for the two-tailed rejection area. The null hypothesis that states that the variance ratio VR_k is statistically indistinguishable from one has to be rejected when the absolute value of the standardized variance ratio $|SVR_k|$ exceeds a critical value for a given significance level α (Witkowska, Matuszewska-Janica, & Kompa, 2012).

3.5.4. Runs test

Runs test is one of the most popular tests that verify the randomness of observations under RW1. With reference to financial markets, the null hypothesis states that the changes in prices are random. The alternative hypothesis states that in the time series analysed, the price changes are not random. The runs test is based on the signs, not on the values. Thus, it does not matter if the price changes or returns are considered (the decreases of prices or negative returns are treated the same by the runs test). The hypotheses verified in the runs test can also be formulated as follows (Osińska, 2006):

$$H_0\colon r_t = \varepsilon_t, \tag{3.76}$$
$$H_1\colon r_t \neq \varepsilon_t. \tag{3.77}$$

There are two commonly applied ways of defining runs of consecutive elements. The runs test can be conducted on the basis of:

a) two defined elements of the runs (Wald-Wolfowitz runs test):
   - symbol A – assigned to a price change/return that is not less than zero ($r_t \geq 0$),
   - symbol B – assigned to a price change/return that is less than zero ($r_t < 0$),

b) three defined elements of the runs:
   - symbol A – assigned to a price change/return that is less than zero ($r_t < 0$),
   - symbol B – assigned to a price change/return that is equal to zero ($r_t = 0$),
   - symbol C – assigned to a price change/return that is greater than zero ($r_t > 0$).

A crucial element of the test is the calculation of the U-statistic. The application of this test is subject to a specific condition, namely, the count of elements in particular runs must equal at least twenty. The U-statistic has a normal distribution. The null hypothesis which states that the changes in the analysed time series are random should be rejected when the absolute value of the U-statistic exceeds a critical value that results from the standardized normal distribution tables. The U-statistic can be formulated as follows:

$$U = \frac{K - E(\widetilde{K})}{S(\widetilde{K})}, \tag{3.78}$$

where:
K – the empirical number of runs,
$E(\widetilde{K})$ – the expected number of runs,
$S(\widetilde{K})$ – standard deviation for a number of runs.

The expected number of runs $E(\widetilde{K})$ as well as the standard deviation for a number of runs $S(\widetilde{K})$ are calculated on the basis of different formulas depending on the variant of defining runs mentioned above. In variant a) which uses two symbols (symbols A and B), the expected number of runs $E(\widetilde{K})$ as well as the standard deviation for a number of runs $S(\widetilde{K})$ are calculated with the use of the following formulas:

$$E(\widetilde{K}) = \frac{2n_1n_2 + n}{n}, \tag{3.79}$$

$$S(\widetilde{K}) = \sqrt{\frac{2n_1n_2(2n_1n_2 - n)}{(n-1)n^2}}. \quad (3.80)$$

In variant b) which uses three symbols (symbols A, B, and C), the expected number of runs $E(\widetilde{K})$ as well as the standard deviation for a number of runs $S(\widetilde{K})$ are calculated using the following formulas (Witkowska, Matuszewska-Janica, & Kompa, 2012):

$$E(\widetilde{K}) = n + 1 - \frac{\sum_{j=1}^{3} n_j^2}{n}, \quad (3.81)$$

$$S(\widetilde{K}) = \sqrt{\frac{\sum_{j=1}^{3} n_j^2 \left(\sum_{j=1}^{3} n_j^2 + n + n^2\right) - 2n\sum_{j=1}^{3} n_j^3 - n^3}{n(n^2-1)}}, \quad (3.82)$$

where:
n – the number of observations (price changes/returns) in the time series analysed,
n_1 – the number of symbols A,
n_2 – the number of symbols B,
n_j – the number of symbols A, B, and C.

3.5.5. Normality tests

Normality tests are used to examine the compatibility of the empirical distribution F with the family of theoretical normal distributions $N(\hat{\mu}, \hat{\sigma}^{\epsilon})$. They are willingly applied in finance in order to check whether the financial time series are normally distributed. The normality tests as the group of the random walk tests refer to the model of Bachelier (1900), in which the continuously compounded returns are i.i.d. normal variates with mean μ and variance σ^2 (Campbell, Lo, & MacKinlay, 1997):

$$p_t = \mu + p_{t-1} + \varepsilon_t, \qquad \varepsilon_t \; i.i.d. \mathcal{N}(0, \sigma^2), \quad (3.83)$$

where:
p_t – a natural logarithm of the price at time t.

Despite the fact that even for low frequency data the actual returns of financial assets rarely fit the normal distribution and the assumption of identically distributed increments is difficult to hold over long time spans, the normality tests are willingly conducted in the studies dedicated to the market efficiency hypothesis testing. They are also often mentioned in textbooks that cover this topic (Osińska, 2006).

In normality tests, the null hypothesis states that the empirical distribution F is compatible with the family of theoretical normal distributions $N(\hat{\mu}, \hat{\sigma}^{\epsilon})$. The alternative hypothesis states that the empirical distribution F is not compatible with the family of theoretical normal distributions $N(\hat{\mu}, \hat{\sigma}^{\epsilon})$. The hypotheses verified by the normality tests can be formulated as follows:

$$H_0: F = N(\hat{\mu}, \hat{\sigma}^{\epsilon}), \tag{3.84}$$
$$H_1: F \neq N(\hat{\mu}, \hat{\sigma}^{\epsilon}). \tag{3.85}$$

Taking into account different constructions of the normality tests, Czekaj (2014) divided them into four groups:

a) nonparametric compliance tests examine the compatibility of the empirical distribution with the normal distribution. This group of tests verifies the distance between the empirical distribution function and the normal distribution function. Tests from this group also allow to compare the compatibility of empirical distributions with other types of theoretical distributions. The examples of tests representing this group are as follows: Kolmogorov-Smirnov test, Liliefors test, and Anderson-Darling test;
b) tests based on the moments of sample using a characteristic feature of the normal distribution, namely, skewness and kurtosis which equal zero. One of the most popular tests representing this group is the Jarque-Bera test;
c) tests based on the measures of the quantile-quantile position use the assumption that for a normal distribution it is expected that the empirical and theoretical quantiles will lie along the line $y = x$. One of the most popular tests representing this group is the Shapiro-Wilk test;
d) χ^2 tests are based on a difference between the empirical and theoretical frequencies of occurrence. One of the most popular tests representing this group is the Doornik-Hansen test.

Among the most popular normality tests in the econometric literature are the Liliefors test, the Shapiro-Wilk test, and the Jarque-Bera test. According to Osińska (2006), these tests are complementary, as the Shaprio-Wilk test is the best for smaller samples, as opposed to the Liliefors test which requires larger samples.

The Liliefors test is based on the Kolmogorov λ-statistic. The critical values of this test can be found in the tables of the λ-Kolmogorov distribution. The Kolmogorov λ-statistic can be formulated as follows:

$$\lambda = \sqrt{T} d_n, \tag{3.86}$$

assuming that:

$$d_n = \max_{x_i} |F(x_i) - S_n(x_i)| \tag{3.87}$$

where:
T – the number of observations,
$F(x_i)$ – normal distribution function,
$S_n(x_i)$ – empirical distribution function.

The Shapiro-Wilk W-test is based on the W-statistic. Its critical values may be found in the tables of the Shapiro-Wilk test. The Shapiro-Wilk W-test can be formulated as follows:

$$W = \frac{(\sum_{i=1}^{[\frac{n}{2}]} a_i(n)(x_{(n-i+1)} - x_i))^2}{\sum_{j=1}^{n}(x_j - \bar{x})^2}, \tag{3.88}$$

where:
x_j – j^{th} observation of variable x,
$\bar{x}$ – the average value of variable x,
$x_{(n-i+1)} - x_i$ – the so-called quasi ranges of order i,
$a_i(n)$ – constant values depending on the count n of the sample and value i.

The Jarque-Bera test constitutes a goodness-of-fit test that verifies if the empirical sample has skewness and kurtosis matching a normal distribution. It is based on the statistic presented below. The distribution of this statistic is compatible with the χ^2-distribution with two degrees of freedom:

$$JB = \frac{n}{6}\left(S^2 + \frac{1}{4}(K-3)^2\right), \tag{3.89}$$

assuming that:

$$S = \frac{\hat{\mu}_3}{\hat{\sigma}^3} = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^3}{(\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2)^{\frac{3}{2}}}, \tag{3.90}$$

$$K = \frac{\hat{\mu}_4}{\hat{\sigma}^4} = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^4}{(\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2)^2}, \tag{3.91}$$

where:
S – the sample skewness,
K – the sample kurtosis,
$\hat{\mu}_3, \hat{\mu}_4$ – the estimates of the third and fourth central moments,
$\hat{\sigma}^2$ – the estimate of the second central moment, i.e., the variance,
$\bar{x}$ – the sample mean,
x_i – i^{th} observation of variable x,
n – the number of observations.

3.6. Calendar effects as a deviation from the market efficiency

The calendar effects consist in repeatable appearing of some anomalies in particular periods, for instance, months, days, or even hours. The anomalies may pertain to, for example, prices, returns, variance, volume, or spreads. The appearance of calendar anomalies may challenge the efficient market hypothesis. They can be modelled and forecasted if they are regular. Osińska (2006) enumerated the following calendar effects observed on financial markets:

a) the effect of January – many empirical studies conducted on the developed markets indicated that returns in January are averagely higher than returns in other months. This phenomenon seems to be caused by the sell-off of the loss-making shares in December and the purchase of the same shares in January. The effect of January mostly pertains to smaller-cap companies;
b) the effect of distribution of returns during the month – the returns are higher in the first half of the month;
c) the effect of Monday and the effect of the weekend – returns on Monday are averagely lower compared to the other days of the week. It is explained by a longer time (weekend between a Friday and a Monday session) for making decision (the effect of the weekend);
d) the effect of the hour during the session – during the first trading hour on Monday the returns are lower compared to the other trading hours. However, during the first trading hour on the other days of the week, the returns are higher compared to the other trading hours. On all days of the week, during the last trading 15 minutes, the returns are higher.

There are many approaches to calendar effects testing. One of the tests that often appears in the issue-related literature is a two-sample test of means. This test begins with the calculation of means and variances of the examined samples. The null hypothesis states that the means are not significantly different. The alternative hypothesis states that the means are significantly different and, thus, the calendar effect appears. The aforementioned hypotheses can also be formulated as follows:

$$H_0: E(y_i) = E(y_j), \tag{3.92}$$

$$H_1: E(y_i) \neq E(y_j). \tag{3.93}$$

To verify the above-mentioned hypotheses, the u-statistic formulated below should be calculated. For larger samples, the u-statistic has a normal distribution. The test requires to make the assumption of equality of variances. It also requires the normality of variables. In the case of smaller samples, the u-statistic has a t-Student distribution:

$$u = \frac{\bar{y}_i - \bar{y}_j}{\sqrt{\frac{S_i^2}{T_i} + \frac{S_j^2}{T_j}}}, \tag{3.94}$$

where:
i, j – period i and j respectively,
$\bar{y}_i, \bar{y}_j$ – the mean of observations in periods i and j, respectively,

S_i^2, S_j^2 – the variance of observations in periods i and j, respectively,
T_i, T_j – the number of observations in periods i and j, respectively.

The calendar effects can be also tested with the use of econometric models. Witkowska, Matuszewska-Janica, and Kompa (2012) proposed an exemplary econometric model dedicated to the verification of the effect of days of the week. The model can also be used successfully for other periods. To test the calendar effects, some more complicated models can also be used, like the models of the GARCH class. The model proposed by Witkowska, Matuszewska-Janica, and Kompa (2012) can be formulated as follows:

$$y_t = \alpha_1 MON_t + \alpha_2 TUE_t + \alpha_3 WED_t + \alpha_4 THU_t + \alpha_5 FRI_t + \varepsilon_t, \tag{3.95}$$

where:
y_t – observation in period t,
$MON_t, TUE_t, WED_t, THU_t, FRI_t$ – variables that take value one on Monday, Tuesday, Wednesday, Thursday, Friday, and for other observations value zero,
α_i – the parameter of the regression function related to a particular day,
ε_t – an error component.

The effect of the week occurs when the parameter α_i significantly differs from zero. When the parameter α_1 significantly differs from zero, it means that the independent variable has a significant impact on the dependent variable y. The null hypothesis states that the parameter α_i equals zero, which means that the independent variable does not have any significant impact on the independent variable y. The alternative hypothesis states that the parameter α_i significantly differs from zero, which means that the independent variable has a significant impact on the independent variable y. Thus, the hypotheses tested can be formulated as follows:

$$H_0: \alpha_i = 0, \tag{3.96}$$
$$H_1: \alpha_i \neq 0. \tag{3.97}$$

The aforementioned hypotheses are tested using the following t-statistic with the Student's t-distribution and for $(n-k)$ degrees of freedom:

$$t = \frac{\hat{\alpha}_i}{S(\hat{\alpha}_i)}, \tag{3.98}$$

where:
$\hat{\alpha}_i$ – the estimation of parameter α_i,
$S(\hat{\alpha}_i)$ – the standard error of the estimation of parameter α_i.

3.7. The random walk testing under more general assumptions

The random walk tests presented in the previous sections of this chapter, such as the autocorrelation tests, the variance ratio tests, and the runs tests, verify the random walk hypothesis under the RW1 assumption. A presented theory has the merit of being simple.

Nevertheless, the actual financial market data do not seem to fit the strict assumptions of RW1. Fama (1970) argued that the market efficiency hypothesis should be verified under more general assumptions, proposing that the most appropriate assumption is the one, that states that the innovation process ε_t is a martingale difference sequence.

Salisu, Oloko, and Oyewole (2016) provided a brief review of methodology applied in the studies dedicated to the martingale hypothesis testing. Among the linear measures they enumerated: the portmanteau test by Ljung and Box (1978), variance ratio test by Lo and MacKinlay (1988, 1989), automatic portmanteau test (AQ) of Escanciano and Lobato (2009), and automatic variance ratio test (AVR) of Kim (2006) who extended the work of Choi (1999). Among the non-linear tests, Salisu, Oloko, and Oyewole (2016) enumerated: the generalized spectral test (GS) of Escanciano and Velasco (2006), and consistent tests of Domínguez and Lobato (2003).

Most of the martingale hypothesis tests are based on the variance ratio tests. A comprehensive review of the variance ratio tests was provided by Charles and Darne (2009). As many other authors, they also discussed one of the most popular variance ratio tests, i.e., the variance ratio tests (VR) proposed by Lo and MacKinlay (1988). The heteroscedasticity robust test statitsic $M(k)$, which follows the standard normal distribution asymptotically under the null hypothesis stating that $VR(k) = 1$, is applicable to returns x_t generated from a martingale difference time series:

$$M(k) = \frac{VR(k) - 1}{\phi(k)^{1/2}}, \tag{3.99}$$

where:

$$\phi(k) = \sum_{j=1}^{k-1} \left[\frac{2(k-j)}{k}\right]^2 \delta(j), \tag{3.100}$$

$$\delta(j) = \left\{\sum_{t=j+1}^{T} (x_t - \hat{\mu})^2 (x_{t-j} - \hat{\mu})^2\right\} \div \left\{\left[\sum_{t=1}^{T} (x_t - \hat{\mu})^2\right]^2\right\} \tag{3.101}$$

$$\hat{\mu} = \frac{\sum_{t=1}^{T} x_t}{T} \tag{3.102}$$

3.8. Studies dedicated to the forecasting of investment fund returns

Based on Wermers (1999), Zamojska (2012) enumerates three significant phenomena related to forecasting of investment fund returns on developed markets:

- the results of funds can be repeated up to one year,
- due to smart money effects, the inflow of funds to investment fund is disproportionately larger,

- the impact of investment strategy of equity investment funds on stock prices implicates a medium-term momentum effect.

According to Wermers (1999) the three above-mentioned phenomena result from the expected price pressure caused by the expected inflow of capital from individual investors to investment funds and then from investment funds to equity market, which eventually appears in the purchase of stocks. Taking into account the significant value of assets under management of institutional investors, such a mechanism can cause demand shocks for particular shares. The first empirical observation of Wermers (1999) that may support this hypothesis is the influence of inflow of funds from institutional investors to stock market on the returns of particular stocks. Based on knowledge coming from the empirical studies, in order to ensure an optimal structure of portfolio, fund managers tend to increase (decrease) assets possessed in response to the inflow (outflow) of funds to (from) investment fund. In addition, the inflow of capital into investment funds is not a random process. Moreover, the purchase of the next assets resulting from the inflow of funds into investment fund does not compensate the sell-off of assets resulting from the outflow of funds from investment fund. The second empirical observation that may support the aforementioned hypothesis proposed by Wermers (1999) is the occurrence of price pressure mechanism resulting from the flows of funds from and to investment funds. The mechanism of price pressure allows to forecast the returns of stocks and investment funds.

The phenomenon of persistence of investment fund performance became popular among investors, fund managers, and economists due to the related momentum effect. The momentum effect is also related to the issue of the verification of the weak-form efficient market hypothesis. The momentum effect is one of the most often examined anomaly of asset pricing in the academic literature. It challenges the efficient market hypothesis even in its weak form and consists in the persistence of financial asset results. Some stock portfolios which in the recent past generated relatively high (low) returns, continued to generate relatively high (low) returns in the near future. This observation was surprising and hard to explain to academics and professionals. Even Fama admitted that the momentum effect constitutes a serious symptom of informational inefficiency, which cannot be explained by the Fama and French model (Czekaj, 2014). Already in the 1960s some studies proposed that the relative results (results generated by particular funds in reference to all funds from a given research sample) of investment funds tended to repeat. Early studies dedicated to the issue of performance persistence suggested that investment funds that belong to the group of the best (worst) funds in the first period often belonged to the same group in the following periods. This phenomenon could continue from a month up to three years. In one of the earliest studies, in which the persistence of funds results was observed, Sharpe (1966) examined a sample of 34 American open-ended mutual funds in years 1954-1963. Sharpe noticed that the results of the best- and the worst-performing funds tended to continue.

Grinblatt and Titman (1992), who conducted a study on the sample of the American investment funds in years 1974-1984, proposed that investment funds that gained the highest (the lowest) returns in the first 60-month subperiod also gained high (low) returns in the following 60-month subperiod. Hendricks, Patel, and Zeckhauser (1993) proposed that the series of similar results appeared among the American investment funds in years 1974-1988. According to their study, the funds that generated the highest returns in the last 12 months tended to generate relatively higher returns within 1 to 8 following quarters. A strategy that aimed to construct a portfolio every quarter using the best-performing funds in last 12 months could generate a higher return compared to the average return of all funds. However, as the authors emphasized, the return from such a portfolio would be just slightly higher than the return of benchmark. The issue of performance persistence appeared also in the case of the lowest returns. The researchers also tried to check whether the persistent results of investment funds could result from the usage of the capitalization effect or P/E ratio by the fund managers. However, the researchers could not explain this issue with some well-known fundamental anomalies of asset pricing. A study by Goetzmann and Ibbotson (1994) provided the additional support for performance persistence hypothesis. The researchers distinguished two equally numerous groups of investment funds from their research sample. The first group contained the so-called ‘winners’, namely, investment funds that generated higher returns than the median return of a whole sample. The second group consisted of the so-called ‘losers’, namely, the funds that generated lower returns than the median of a whole sample. The results of this study indicated that in the following periods it was unlikely that the funds would change their group. By repeating the study using risk-adjusted returns, the researchers also proposed that performance persistence among the ‘winners’ cannot be explained by the application of some risky strategies delivering higher returns. Some explanations for the occurrence of performance persistence among investment funds were delivered by Grinblatt, Titman, and Wermers (1995) who proposed that a significant part of fund managers seems to apply similar strategies. Thus, their results are also similar. Moreover, the researchers suggested that investment fund managers tend to exploit the momentum effect that occurs in the stock markets. Fund managers do it by investing in shares taking into account their returns from the recent past. The explanation of persistence of investment fund results with the application of similar strategies by fund managers was also supported by Brown and Goetzman (1995). Elton, Grubber, and Blake (1996) proposed that the effect of persistence of investment funds results can last even longer, i.e., up to three years. They also proposed that this effect may occur in the case of all funds, not only in the case of the best- and the worst-performing ones. Carhart (1997) proposed that transaction costs, intensity of transactions, and the application of the momentum strategy explain most of differences between the results of the best- and the worst-performing funds. The researcher applied a Fama and French model enriched with the indicator referring to momentum effect. At the same time, the researcher proposed that the results of the study gave no grounds to state that the persistence of the relative results of investment funds can be explained by significantly high or low skills of fund managers. Based on a broad sample of equity funds covering years 1962-1993, Carhart (1997) suggested the occurrence of a short-term persistence of investment fund results.

Moving on to more recent studies, Philpot, Heath, and Rimbey (2000) applied a modified approach using 4-field tables of conditional count in the study on 73 US bond investment funds. The researchers received results supporting the occurrence of persistence of investment fund results. The fund performance persistence hypothesis was also supported by the results of the study on some developed European markets conducted by Silva, Cortem, and Armada (2005). The researchers examined bond investment funds operating on some developed European markets in terms of the occurrence of performance persistence effect. They used data from years 1994-2000. The researchers came to conclusions that performance persistence effect commonly appeared among the examined bond funds. Nevertheless, the persistence of bad results was much stronger compared to the persistence of good results. Bollen and Buse (2005) presented the results that confirm the occurrence of performance persistence in short quarterly periods. At the same time, the authors proposed that the issue of the short-term performance persistence is economically insignificant due to high transaction costs related to the purchase and sale of the participation unit. Droms and Walker (2006) received similar results for 2-year subperiods in the study on bond funds investing in the governmental and corporate bonds in years 1990-1999. Polwitoon and Tawatnuntachai (2006) observed the persistence of investment fund results in 1-year and 3-year subperiods, in the study on the US funds investing in the foreign bonds, using data from years 1993-2004. Du, Huang, and Blanchfield (2009) examined the persistence of results of the US funds investing in corporate bonds in years 1992-2003. Their study also supported the performance persistence hypothesis for a couple of short-term subperiods. Otten and Thevissen (2011), who analysed the most developed European markets, proposed that strategy based on investing in the best-performing funds and selling the worst-performing ones brings abnormal returns. This strategy is profitable for both the 6-month and 12-month periods.

The studies on the persistence of investment fund results were also willingly conducted on the Polish market. For example, a study conducted on 19 funds for 3-month ranking periods by Patena and Żołyniak (2008), did not support the performance persistence hypothesis in the examined sample of equity funds in the period 2004-2007. However, the performance persistence hypothesis was supported in the study by Jackowicz and Filip (2009) on the equity funds. Using Jensen's alpha, Swinkels and Rzezniczak (2009) observed the occurrence of performance persistence in the examined group of hybrid and bond funds. In the sample of hybrid and bond funds, also Białkowski and Otten (2011) observed a short-term persistence of results. Skrodzka (2014), in the study on bond funds, proposed that the persistence of results did not occur. However, the high volatility of returns in the research period of 2011 could have a significant impact on changes in the ranking of investment funds.

The studies discussed above were dedicated to the examination of the performance persistence effect, a well examined and very popular anomaly also pertaining to investment funds. This asset pricing anomaly also constitutes a deviation from the efficient market hypothesis, even in its weak form. Further considerations refer other studies that examined the forecasting features of returns of investment funds. Discussed studies applied methods of the EMH testing discussed earlier in this chapter.

Zamojska (2012) examined the forecasting features of 13 selected open-ended equity investment funds operating on the Polish stock market in the period from January 2000 to December 2010. The study began with the analysis of statistical features of monthly excess returns of investment funds. The analysis of stationarity of monthly excess returns was conducted with the use of the augmented Dickey-Fuller test (ADF). The optimal lag order of the auxiliary regression was chosen on the basis of the modified Akaike criterion (MAIC). The significance level of the ADF test was set at 0.05. The results of test indicated that the null hypothesis had to be rejected. The null hypothesis of the ADF test states that the unit root appears in the analysed time series. Hence, monthly excess returns could be considered stationary. Additionally, in order to examine the occurrence of some of stylized facts, i.e., the characteristic features of financial time series, the author also presented the coefficients of skewness and kurtosis. The coefficients confirmed the occurrence of negative skewness and leptokurtosis, which constitute characteristic features of financial time series. The researcher additionally noticed that the occurrence of these stylized facts implicated the possibility of forecasting of the examined financial time series. In the next part of the study, the author aimed to examine the forecasting features of returns. Thus, the author verified the null hypothesis, stating that the time series of returns constituted the martingale increments. To verify the martingale hypothesis, the author applied the variance ratio test of Lo and MacKinlay for the overlapping subperiods and the test of signs by Wright. The variants of the applied tests took into account the occurrence of heteroscedasticity and autocorrelation in the time series of returns of investment funds. The results of the variance ratio tests indicated that only in the case of 4 funds there were no grounds to reject the null hypothesis, stating that returns constituted the time series of the martingale increments. Thus, they were informationally efficient in a weak form, and there was no possibility to forecast them on the basis of the historical observations. It also suggests that investing in these funds on the basis of their historical performance did not give any possibility to gain abnormal returns. However, in the case of the other funds, at least one test suggested to reject the null hypothesis. Hence, they could be considered informationally inefficient in a weak form.

Rompotis (2011) made an attempt to assess the weak-form efficiency of the equity-linked Exchange Traded Funds traded on the US stock market. The research sample consisted of 66 equity-linked ETFs traded on the US stock market in the period 2001-2010. The analysed time series consisted of daily returns calculated from the net asset value. The researcher verified the weak-form efficiency hypothesis with the use of both parametric and nonparametric tests aiming to answer a question whether the returns of the analysed ETFs followed a random walk. Among the parametric tests applied were: autocorrelation test, serial correlation test, Augmented Dickey-Fuller unit root test. The only nonparametric test applied in the study was the Phillips-Peron unit root test. The rejection of the weak-form efficient market hypothesis was supported by the estimated autocorrelations. However, according to serial correlation tests, most funds were efficiently priced. Results provided by both unit root tests used in the study, i.e., the Augmented Dickey-Fuller unit root test and the Phillips-Peron unit root test, indicated the non-existence of the unit root in the examined time series. Thus, the unit root tests supported the indications of the serial correlation tests, suggesting that the weak-form efficient market hypothesis could not be rejected.

The study by Anoruo and Elike (2008) aimed to examine the random walk behaviour of four Chinese non-US equity closed-end funds (Greater China Fund (GCH), China Fund (CHN), Jardine Fleming China Region Fund (JFC), and Taiwan Greater China Fund (TFC)), especially with the use of joint variance ratio tests. The analysed time series consisted of monthly returns of four funds covering the period from May 1989 to May 2007. Prior to the application of joint variance ratio tests, the researchers applied the individual variance ratio tests advanced by Lo and MacKinlay (1988), and Wright (2000). Then the researchers applied the joint variance ratio frameworks proposed by Kim (2006), Chow and Denning (1993), and Whang and Kim (2003). Both individual and joint variance ratio tests indicated to reject the null hypothesis stating that the returns of four closed-end funds followed a random walk. To check the robustness of results provided by the variance ratio tests, the researchers also applied the runs test which provided consistent results indicating that the analysed time series did not follow the random. The study clearly indicated that the weak-form efficiency hypothesis did not hold for the analysed funds.

Gregoriou, Rouah, and Serdzro (2003) made an attempt to answer a question if the hedge fund returns followed the random walk process. The research sample consisted of 1484 hedge funds that reported the results to the LaPorte Asset Allocation System/Zurich Capital Markets database. The analysed time series consisted of the monthly returns of hedge funds covering the period from January 1991 to December 2000. The calculations were not done for the returns of each hedge fund separately, but for the monthly median returns of eight hedge fund classes, distinguished taking into account their strategy. In order to test the random walk hypothesis, the researchers applied the Augmented Dickey-Fuller test with the procedure proposed by Pindyck and Rubinfeld (1998) which additionally adjusts the ADF test specifically for testing random walk. The researchers found the evidence of random walk in all classes of hedge funds, except for the Market Neutral class which attempts to achieve a net-zero exposure to systematic risk factors. Based on the results of the study, the researchers suggest that due to the weak-form informational efficiency of most hedge fund classes there is no possibility to forecast their future returns on the basis of the historical time series of returns.

Mamede and Malaquias (2017) applied another approach to examine the weak-form informational efficiency of funds, i.e., the verification of calendar effects. In the case of this study, the researchers examined the occurrence of the Monday effect in returns of Brazilian hedge funds with immediate redemption. The research sample consisted of 2162 Brazilian hedge funds that did not have redemption restrictions. The analysed time series included daily simple returns of hedge funds from January 2005 to March 2014. As a main tool for examining the Monday effect, the researchers used a multiple regression analysis with panel data and random effects. The Jarque-Bera test indicated that the returns were not normally distributed.

Due to the indication of the normality test and taking into account the requirements of the regression analysis, the Winsorizing procedure was performed. After the Winsorizing procedure, the distribution of returns was much more fitted to a normal distribution. Moreover, the researchers examined the stationarity of returns using the unit root test proposed by Levin, Lin, and Chu (2002). The applied test indicated that the returns were stationary. The average daily returns in particular days indicated that on Monday the average returns were the lowest. The results of the regression analysis with panel data and random effects indicated that on average the profitability on Monday was statistically lower compared to the other days of the week. As a robustness check, the model was estimated once again using the logarithmic returns. The result turned out to be very similar.

3.9. The critique of the efficient market hypothesis and econometric difficulties related to the efficient market hypothesis testing

Fama (1970), proposing the efficient market hypothesis, has started a discussion which lasts to this date. Many studies taking part in the discussion on the market efficiency are focused on informational efficiency testing. Using many different methodological approaches, they try to answer a question whether the markets are informationally efficient or not. In the other group of papers, researchers directly challenge the definition of the efficient market proposed by Fama and suggest some adjustments, or a completely new approach to defining the market efficiency.

In one of the most frequently cited papers that constitutes a critique of the efficient market hypothesis, Grossman and Stiglitz (1980) propose that investors must be rewarded with some extra risk-adjusted returns for incurring the costs of information collection and analysis. Therefore, they emphasize the significance of data collection and analysis costs. If a rational investor had no chance of being compensated, he would not incur such expenses. In their model, investors have to pay for information that is relevant in terms of asset pricing. The information can be observed by the uninformed investors through the informative price system. In the model proposed by Grossman and Stiglitz, markets cannot be fully informationally efficient.

In another frequently cited paper that constituted a critique of the efficient market hypothesis, Shleifer and Vishny (1997) argue with the efficient market hypothesis, and state that the arbitrage opportunities do not exist. The concept of arbitrage from the textbook is actually different from the reality, as in practice the arbitrage is usually both costly and risky. Nowadays, a group of arbitrageurs mainly consists of highly specialized professional institutions. It is especially due to the short timeframe in which the arbitrage opportunities occur. Thus, generating significant returns from the arbitrage is a domain of the high-frequency traders (Budish, Cramton, & Shim, 2015).

The efficient market hypothesis testing requires defining normal returns against which the residuals could be computed. The problem is that the theoretical model that determines the normal returns can be misspecified. It leads to the joint hypothesis problem. If the market efficiency hypothesis is rejected, it is unknown whether the market is inefficient or the theoretical model that determines the normal returns is misspecified. Thus, the efficient market hypothesis can never be rejected, which means that it is not falsifiable.

The next issue pertaining to the efficient market hypothesis testing is related to the information set tested, which can be uninformative. The non-rejection of the efficient market hypothesis using a smaller information set I_t, which is a part of a bigger information set J_t ($I_t \subseteq J_t$), can be caused by choosing the uninformative smaller information set I_t (Linton, 2019).

3.10. Conclusions

This chapter discusses a theoretical background staying behind the efficient market hypothesis. It also provides the overview of methodology applied in studies dedicated to weak-form efficient market hypothesis testing. The emphasis was put especially on the econometric tools used for the weak-form efficient market hypothesis testing. Nevertheless, other approaches applied in the issue-related studies were also discussed. Due to commonly applied random walk tests under such strict assumptions as RW1, despite the fact that the real data do not seem to fit them well, a particular attention was paid to the need of relieving assumptions under which the weak-form efficiency tests are performed. Fama (1970) argued that the efficient market hypothesis should be verified under more general assumptions. He proposed that the most appropriate assumption is the one, which states that the innovation process ε_t is a martingale difference sequence.

Most importantly, this chapter provides a theoretical background for developing a research methodology that aims to verify a supplementary research hypothesis H2, which states that the weak-form informational efficiency of quantitative funds is higher than the weak-form informational efficiency of qualitative funds. A developed methodology will also be used to answer some supplementary research questions posed in the introduction. It will also play an important role in terms of a study on the performance of quantitative funds, due to the evaluation of the applicability of some performance measures that require the normality of returns. A developed methodology will also be used to indicate the periods of a low weak-form informational efficiency of equity markets (the selected benchmarks of examined investment funds). It will be important in terms of verification of hypothesis H3, which states that quantitative funds perform better than qualitative funds in periods of a low weak-form informational efficiency of equity markets. Econometric tools presented in this chapter will allow to examine the features of returns of quantitative funds within the context of the weak-form informational efficiency.

4. Theoretical background for the evaluation of the performance of quant funds

This chapter provides a theoretical background for the evaluation of the performance of quantitative funds. Knowledge presented in this chapter allows for a better understanding of methods applied in the study on performance of quant funds, which was conducted for the needs of this thesis. The aforementioned study aims to verify performance-related hypotheses, namely, hypothesis H1 (the main research hypothesis), which states that the performance of quantitative funds is higher than the performance of qualitative funds, as well as hypothesis H3 (a supplementary research hypothesis), which states that quantitative funds perform better than qualitative funds in periods of low weak-form informational efficiency of equity markets. Furthermore, the knowledge presented in this chapter supported the development of methodology, which allowed to answer a series of supplementary research questions posed in the introduction.

The theory and tools from the area of portfolio performance evaluation presented in this chapter can be perceived as classic, willingly applied in studies pertaining to portfolio performance evaluation even these days. Tools presented in this chapter were also applied in studies strictly related to the problem addressed by this thesis, i.e., the performance of quantitative funds, where the following examples can be mentioned: Chincarini (2014), Harvey et al. (2017), Parvez and Sudhir (2005), Chuang and Kuan (2018).

One of the most important terms in this thesis, namely, the term *performance,* commonly used in the English-language literature pertaining to the evaluation of the activity of economic units, refers to the outcomes of activities taken in a specific time period. In this thesis, the applied term *performance* refers to the outcomes of portfolio management in a specific time period. A process of evaluation of results generated by investment funds is referred to as a *performance evaluation process*. It provides information on historical results and investment-related costs (Zamojska, 2012).

Jajuga and Jajuga (2008) propose that portfolio performance evaluation involves three areas:

- performance measurement i.e., the measurement of portfolio performance with the use of a set of relevant quantitative techniques,
- performance attribution i.e., the analysis of sources of portfolio management performance,
- performance presentation i.e., the presentation of results pertaining to portfolio performance evaluation in a clear and accurate way.

The first of the abovementioned areas of portfolio performance evaluation namely, performance measurement is an ex-post analysis which can be perceived as a set of techniques which allow for a quantitative measurement of return from investment, its risk exposure, and the way in which the return was generated. Performance measurement is applied to evaluate the historical results of funds and portfolio managers using the returns, risk, and correlation structure between the portfolio and its benchmark. In addition, the information gathered using performance measurement can be used in the forecasting of future results (Zamojska, 2012).

The second of the abovementioned areas of portfolio performance evaluation, i.e., performance attribution, consists in the identification and quantification of sources of portfolio management results. The identification of sources of portfolio management results is often subjective. Similarly as in the case of the first area of performance evaluation, performance attribution provides information on results generated with regard to benchmark and sources of results (Feibel, 2003).

The third of the abovementioned areas of portfolio performance evaluation, namely, performance presentation, refers to the presentation of results of portfolio performance evaluation, which should be reliable, clear, and adjusted to a specific audience. Some standards referring to this area have already been developed, such as the Global Investment Performance Standards by CFA Institute (Bacon, 2008).

Following Lawton (2009), Zamojska (2012) indicated the three stages of the portfolio performance evaluation process:

- performance measurement,
- performance attribution,
- performance appraisal i.e., the examination of whether the results came from the skills of the portfolio manager or were independent of the portfolio manager's skills (the results were just a matter of coincidence).

Researchers do not adhere to a single definition or approach to portfolio performance evaluation. Thus, in many cases, portfolio performance evaluation may be understood in a different way compared to the ones proposed by Jajuga and Jajuga (2008) or Zamojska (2012). Some researchers rather try to develop the theory introducing their own view on this matter, where Feibel (2003) can be one of such examples.

4.1. Performance measurement

Performance measurement, as the area of fund performance evaluation, utilizes quantitative techniques to evaluate the performance of portfolio management. Performance measurement commonly and mainly uses simple performance measures, which allow to answer a question whether portfolio performed well accounting for risk, and how it compares with the other portfolios (Christopherson, Carino, & Ferson, 2009).

In the process of choosing an appropriate performance measure or even in the process of performance measure development, it is important to take into account some additional criteria of evaluation like investment time horizon, risk aversion level, expected return, relation between accessible investments, or other criteria taken into account in the process of portfolio construction.

Two basic types of portfolio performance measures can be distinguished:

- the absolute measures of performance,
- the relative measures of performance.

Absolute performance measures are calculated on the basis of portfolio returns. Among the absolute performance measures, such measures as portfolio rate of return and Jensen's alpha, as well as its variations, can be distinguished. Unlike Jensen's alpha, a simple rate of return does not account for the risk of the portfolio.

Relative performance measures are calculated on the basis of predefined reference endogenous and exogenous portfolios. They are basically the ratios of the results and the risks. To put it simply, relative performance measures utilized by performance measurement compare results generated with outlays incurred. In terms of portfolio management, results generated refer to return from portfolio, and outlays incurred refer to risk of portfolio. Such defined relative measures of portfolio performance are also referred to as cardinal measures which can be used to calculate ordinal measures indicating the position of portfolio in the ranking of similar portfolios (Zamojska, 2012).

4.1.1. Asset pricing models as a base for the construction of portfolio performance measures

Asset pricing models, and especially their basic versions, are widely applied in studies related to the evaluation of portfolio management performance. In terms of portfolio performance evaluation, they are used especially to estimate an expected return from portfolio, also called a normal portfolio return. They are also used to estimate an abnormal portfolio return and to construct some portfolio performance measures (Dębski, 2014).

Asset pricing models answer the question of whether the return from investment is adequate to the risk taken. They are a function of factors that affect the expected return from the portfolio. Asset pricing models indicate an expected return as a sum of products of risk premiums (price of risk factor) and quantity of a risk. The aforementioned abnormal return calculated with the use of asset pricing models as a difference between the actual returns and expected returns, constitutes a measure of performance of the active portfolio management. Abnormal returns constitute a justification for the operations of actively managed funds. They are also a basis for the additional renumeration of portfolio managers (Feibel, 2003).

Shukla (2004) proposes that there are two ways in which active managers make an attempt to add value to their shareholders (which basically describes the essence of active portfolio management):

a) constructing portfolio in such a way that it provides a superior risk-return trade-off,
b) continuously monitoring market conditions and revising portfolios in response to changes in the market environment.

Active managers believe to possess skills in both of the abovementioned areas which lead them to generate higher returns to their shareholders compared to returns which could be generated by passive strategies or just benchmarks like the equity indices. Passive strategies, which are often considered contrary to active strategies, aim to track a preselected index (Al-Aradi & Jaimungal, 2021).

From the point of view of an investor, it is important to indicate if portfolio generated abnormal returns, which at least in part will be paid to investor after accounting for commission and taxes. Moreover, from the point of view of an investor, it is important to make an attempt to answer a question whether a fund will be able to generate an abnormal return in the future, and of course whether at least in part it will be paid to investor after accounting for commission and taxes.

Nevertheless, taking into account the efficient market hypothesis, the financial assets should be correctly valued and thus there should be no possibility to generate abnormal returns regularly. In the informationally efficient market, abnormal returns are just a matter of coincidence. In fact, opinions pertaining to informational efficiency of financial markets differ among researchers and practitioners. However, some investors still try to identify portfolio managers who have outstanding skills or possess inside information, which helps them generate abnormal returns.

Behavioural finance looks for sources of abnormal returns in the behaviour of market participants. In the theory of behavioural finance, abnormal returns, treated as asset valuation errors, are caused mainly by interactions between rational and irrational market participants. The existence of irrational market participants is assumed a priori in behavioural finance. This assumption violates one of the basic assumptions of classic finance, namely, the assumption of the rationality of market participants. Finding managers who can generate abnormal returns is a basic goal of portfolio management performance evaluation of investment fund participants. However, the evaluation of portfolio management performance is limited as in the process of portfolio management performance evaluation, the net asset value (NAV) sold by the fund is applied and therefore there is the possibility that the outstanding skills of a portfolio manager will not be included in the participation unit (Zamojska, 2012).

After explaining the terms of *normal return* and *absolute return,* which are important in terms of asset pricing models and portfolio performance evaluation, it is also worth explaining the term of *excess return,* which refers to the difference between the actual return of the asset/portfolio and the return from the risk-free asset. The excess return can often be met in asset pricing models and the relative measures of portfolio performance.

The Capital Asset Pricing Model (CAPM) independently proposed by William Sharpe, John Lintner, Jan Mossin, and Jack Treynor in the mid 1960s constitutes one of the first asset pricing models and one of the most willingly applied models in the studies dedicated to the evaluation of portfolio management performance. What is even more important, the CAPM model constituted a basis for the development of the capital asset pricing theory and was a subject of many considerations, academic discussion, and adjustments. As a capital market model, the CAPM model proposes a description of capital assets behaviour in the market of rational investors. Moreover, as a pricing model, the CAPM model defines the returns of capital assets in the market equilibrium (Sopoćko, 2010).

The CAPM model has the following underlying assumptions (Jajuga & Jajuga, 2008):

- there are no transaction costs and taxation of transactions made,
- assets available on the market can be divided into smaller parts so that any funds can be invested,
- the market prices of assets result from the operations of all investors, and there is no single investor who could affect asset prices solely,
- investors require the same set of information in order to make investment decisions, as their individual decisions are based on the expected returns and risk,
- investors can invest in risk-free assets that give them the same risk-free rate. They can also take loans at the same risk-free rate,
- investors make investment decisions for the same time period,
- all investors have the same and instant access to information,
- the expectations of investors are homogenous, i.e., their estimations of the expected returns, risk, and correlations are the same.

Two basic relationships fill a basic role in the CAPM model:

- The Capital Market Line (CML) representing the relationship between total risk and portfolio return. It also represents efficient portfolios,
- The Security Market Line (SML) representing the relationship between systematic risk measured by the beta ratio and the security rate of return. It also represents portfolios priced correctly.

The CAPM model considers rational investors who invest in efficient portfolios, i.e., portfolios represented by the capital market line (CML), which indicates portfolios combining risk and return optimally. The capital market line depicts portfolios optimally combining risk-free assets and the market portfolio of risky assets. In the CAPM model, investors lend or borrow at the risk-free rate choosing their position on the capital market line, maximising return for a particular risk level. The capital market line can be formulated as follows (Miziołek, 2013):

$$r_i = r_f + \frac{r_m - r_f}{\sigma_m}\sigma_i, \tag{4.1.}$$

where:

r_i – the expected return of the efficient portfolio i,

σ_i – the standard deviation (total risk) of the efficient portfolio i,

r_m – the expected return of the market portfolio,

σ_m – the standard deviation of the market portfolio,

r_f – the return of the risk-free asset.

An exemplary capital market line (CML) of the CAPM model is shown in Figure 4.1.

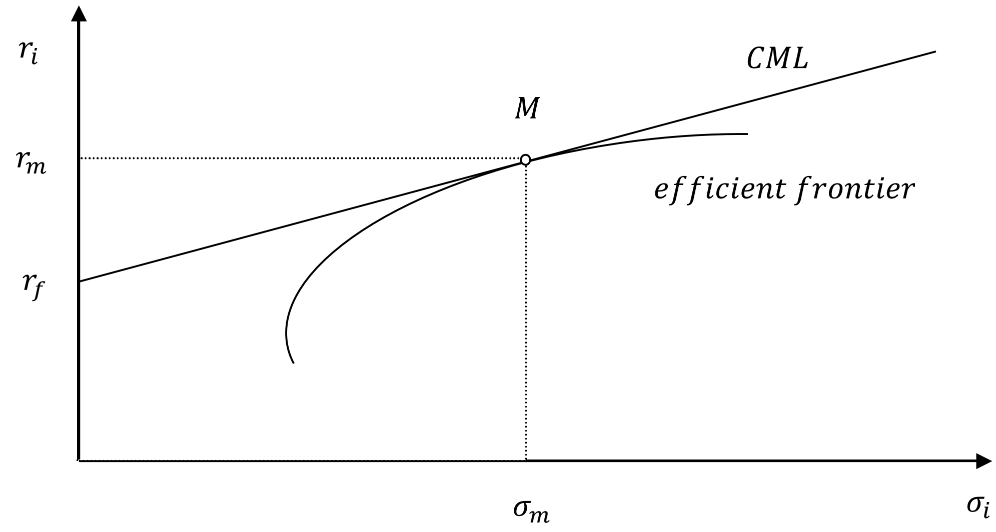

Fig. 4.1. A graphical presentation of an exemplary capital market line (CML) of the CAPM model. Source: Author's own study.

Referring to Figure 4.1., the efficient frontier represents portfolios that can be created using combinations of stocks only. Portfolios comprising stocks and risk-free assets lie on the line connecting the point r_f (risk-free rate) with any point referring to the portfolio of stocks. The capital market line (CML) dominates other lines and is tangent to the efficient frontier in point M, which refers to a market portfolio consisting only of stocks. It suggests that on the stock market, the market portfolio should be desired. The CML line represents efficient portfolios. Shifting to the left of the CML line represents an increasing share of risk-free instruments in the efficient portfolio. It also means that investor becomes a creditor lending money to the issuer of a risk-free asset. Shifting to the right on the CML line represents borrowing money at the risk-free rate (Christopherson, Carino, & Ferson, 2009).

Another important line resulting from the CAPM model, i.e., the security market line (SML), formulates relation between return from portfolio and the systematic risk of portfolio, which constitutes just a part of the total risk of portfolio. Investors aim to construct and hold diversified portfolios, and thus, they aim to eliminate specific portfolio risk of particular assets. The security market line can be expressed with the following formula:

$$r_i = r_f + \beta_i(r_m - r_f), \tag{4.2.}$$

where:
β_i – the systematic risk of the efficient portfolio i,

The security market line (SML) constitutes the equation of the market equilibrium that shows how the market of rational investors behaves when the investors act in line with the principles of portfolio theory. It is also a formula of capital asset pricing that indicates an expected (normal) return from asset/portfolio under the conditions of equilibrium (Jajuga & Jajuga, 2008).

An exemplary security market line (SML) of the CAPM model is depicted in Figure 4.2.

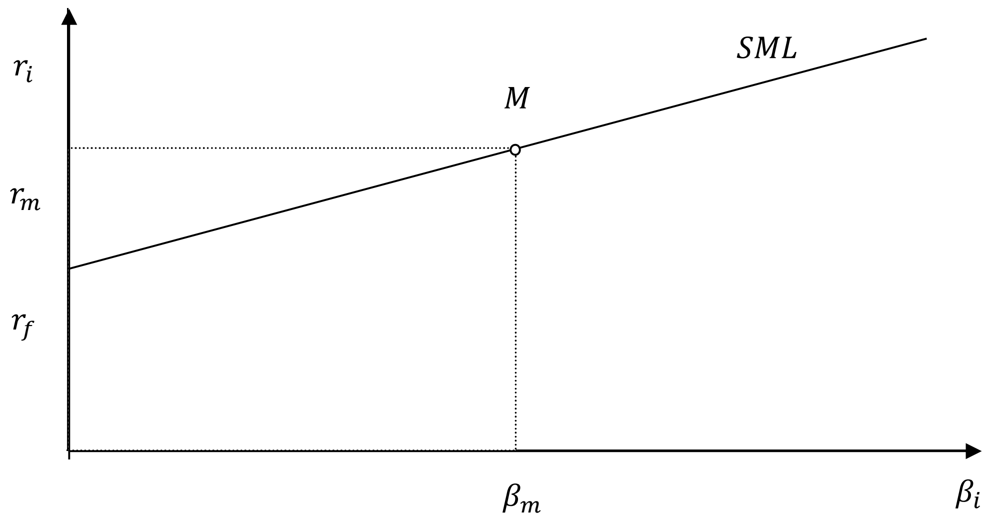

Fig. 4.2. A graphical presentation of an exemplary security market line (SML) of the CAPM model. Source: Author's own study.

The security market line (SML) represents portfolios priced correctly. Referring to Figure 4.2., point M refers to the market portfolio for which β equals 1. Portfolios laying on the SML line are priced correctly i.e., the expected return from this portfolio is in line with a return resulting from the CAPM model. The points above the SML line represent the unpriced portfolios. Such assets are attractive to investors who will buy them, increasing prices of the asset and decreasing their return. Eventually, pricing of these assets will be in line with pricing resulting from the CAPM model (they will be laying on the SML line). The points below the SML line represent the overpriced portfolios. Such assets are unattractive to investors who will sell them, decreasing prices of the asset and increasing their return. Eventually, pricing of these assets will be in line with pricing resulting from the CAPM model as well (they will be laying on the SML line) (Christopherson, Carino, & Ferson, 2009).

If the market portfolio is efficient, then, the expected return from the asset/portfolio meets the equation of the econometric CAPM model formulated as follows:

$$r_{it} - r_{ft} = \alpha_i + \beta_i\left(r_{mt} - r_{ft}\right) + \varepsilon_{it}, \tag{4.3.}$$

where:
α_i – constant term also known as Jensen's alpha,
β_i – systematic risk measure referring to asset/portfolio i,
r_{it} – the return of the asset/portfolio i in time t,
r_{ft} – the return of the risk-free asset/portfolio in time t,
$r_{it} - r_{ft}$ – the excess return of the asset/portfolio i in time t,
r_{mt} – the return of the market portfolio in time t,
ε_{it} – random component.

The tests of the CAPM model were willingly conducted in the following years after issuing original CAPM-related publications. The tests have shown that the CAPM model did not accurately explain the behaviour of the market and its modifications were proposed. The modifications of the CAPM model pertained especially to the analytical expression of the model and its formal assumptions. Then, in the studies raising the issue of the asset pricing models, researchers made an attempt to include some aspects of behavioural finance and issues that appeared along with the development of institutional investors, especially in the early 1990s. Zamojska (2012) indicated four different directions of studies dedicated to asset pricing models:

1. the modifications of the analytical expression of the CAPM model based on results received in its empirical verification, which indicated many deviations from the forecasts of asset/portfolio returns,
2. the development of theoretical validations of the CAPM model, which allowed for its application in multi-period pricing, developing the conceptual grounds of the CAPM model in a theoretical way,
3. attempts to explain deviations from the CAPM model and other anomalies with the use of behavioural approach and by stating the hypothesis that investors systematically do not try to rationally maximise utility function of wealth,
4. approach assuming that asset pricing is heavily related to the goal function of a portfolio manager and not with the utility function of a portfolio manager. This approach poses the question of whether delegating investment decisions from individual investors to professional portfolio managers affects the classic approach to asset pricing.

In the first of the above-mentioned directions of studies dedicated to financial asset pricing, the attempts were made to explain deviations from the forecasts of the asset/portfolio returns, especially with the use of other variables reflecting systematic risk, alternative to market portfolio. Adjustments of the CAPM model changed its assumptions. Nevertheless, the overall expression and theoretical grounds of the model remained preserved. Among variations of the CAPM model proposed in the 1970s, the following ones can be mentioned: zero-beta CAPM, two-factor model, model with included taxation, inhomogeneous expectations model.

Observing and documenting market anomalies, such as the momentum effect, higher returns of small-cap and value stocks, i.e., stocks featured, for instance, by high dividend yield, low price-to-book ratio, and low price-to-earnings ratio, resulted in the development of such adjusted CAPM models as Fama–French three-factor model and Carhart four-factor model in the 1990s.

The Fama–French three-factor model adjusts the CAPM model to include market anomalies, such as the higher returns of small-cap stocks and stocks with a higher book-to-market ratio. The Fama–French three-factor model includes additional independent variables such as: difference between the returns of large-cap and small-cap stocks (SMB_t) as well as difference between the returns of stocks with high and low book-to-market ratio (HML_t). This model can be formulated as follows:

$$r_{it} - r_{ft} = \alpha_i + \beta_{1i}(r_{mt} - r_{ft}) + \beta_{2i}SMB_t + \beta_{3i}HML_t + \varepsilon_{it}, \quad (4.4.)$$

where:
SMB_t – difference between the returns of large-cap and small-cap stocks in time t,
HML_t – difference between the returns of stocks with high and low book-to-market ratios in time t.

Carhart extended the Fama–French three-factor model by adding one more independent variable MOM_t (the monthly momentum factor) that accounts for momentum effect, i.e., anomaly consisting in repeating of generated returns. A momentum factor, namely, MOM_t, can be calculated by subtracting the average returns of the worst performing stocks from the average returns of the best performing stocks, lagged one period. The Carhart four-factor model can be formulated as the following equation:

$$r_{it} - r_{ft} = \alpha_i + \beta_{1i}(r_{mt} - r_{ft}) + \beta_{2i}SMB_t + \beta_{3i}HML_t + \beta_{4i}MOM_t + \varepsilon_{it}, \tag{4.5.}$$

where:
MOM_t – difference between the average returns of the best performing stocks and the average returns of the worst performing stocks in time t.

The Fama–French three-factor model and the Carhart four-factor model constitute the most basic extensions of the classic CAPM model. Nevertheless, these models do not exhaust the topic of the modifications of analytical expression of the CAPM model based on the results obtained in its empirical verification, which indicated many deviations from the forecasts of asset/portfolio returns. An example of an another willingly applied multi-factor model that constitutes a modification of the classic CAPM model is a five-factor asset pricing model by Fama and French (2015).

Referring to the second of the above-mentioned directions of the studies dedicated to capital asset pricing models, one of the most popular outcomes of this research area was the arbitrage pricing theory (APT), also called the arbitrage pricing model (APM). It was introduced in 1976 by Stephen Ross. The APT has fewer assumptions compared to the CAPM model and thus, it is considered to be easier in theoretical comparison but more difficult in practical applications. The APT repeals the assumption that investors make decisions on the basis of the average returns and variances of portfolios. Instead, a new assumption of preferable investment with higher return was introduced. The APT primarily assumes that the law of one price and the arbitrage apply in the market. To put it simply, on the financial markets it can come to arbitrage, namely, a situations when investors make profits from different market valuations of the same assets listed on different markets. The actions of arbitrageurs, i.e., creating demand in the market where the price is lower and creating supply in the market where the price is higher, result in the equalisation of prices, which means that the law of one price holds. Explaining the law of one price in a different way, two assets with the same risk eventually should generate the same return.

The following multi-factor model related to the APT describes the sensitivity of asset/portfolio returns to changes in selected risk factors:

$$r_{it} - r_{ft} = \alpha_i + \beta_{mi}(r_{mt} - r_{ft}) + \beta_{1i}F_{1t} + \beta_{2i}F_{2t} + \cdots + \beta_{ki}F_{kt} + \varepsilon_{it}, \quad (4.6.)$$

where:
F_{jt} – risk factor k that affects asset/portfolio returns in time t.

One of the ATP-based models that are willingly applied in studies related to portfolio performance evaluation is the 7-factor model proposed by Fung and Hsieh (2004). Its modified version was applied in the study related to the comparison of performance of quantitative and qualitative funds by Chincarini (2014). In the original version, the model was applied in the issue-related study by Chuang and Kuan (2018).

As proposed by Harvey (1989), the parameters of the asset pricing models can vary over time. In these cases, the application of conditional asset pricing models is justified. They take into account the changing environment that affects asset pricing.

4.1.2. Absolute portfolio performance measures

Studies dedicated to portfolio performance evaluation focus especially on two basic skills of a portfolio manager, namely selectivity and market timing. Managers who master these two skills should perform better compared to other portfolio managers. A portfolio manager utilizing selectivity skills indicates which financial instruments are overvalued and undervalued. Based on such indications, a portfolio manager selects financial instruments to an investment portfolio. The valuation of financial instruments among managers with selectivity skills is often conducted with the use of fundamental analysis. Selectivity is strictly related to portfolio diversification that aims to reduce specific risk. Market timing refers to the ability to forecast market movements, which aims to choose a right moment for concluding transaction (Zamojska, 2012).

A basic and commonly applied approach to selectivity measurement consists in the application of a constant term (also known as alpha) that appears in the unconditional assets pricing models. The alpha is also considered a portfolio performance measure. Jensen's alpha derived from a classic unconditional CAPM model constitutes an example of one of the most popular absolute portfolio performance measures, also often considered a selectivity measure. Jensen's alpha coming from a classic CAPM model can be defined with the following formula (Aldridge, 2010):

$$\alpha_i = r_{it} - r_{ft} - \beta_i(r_{mt} - r_{ft}) - \varepsilon_{it}, \quad (4.7.)$$

where:
α_i – Jensen's alpha of the asset/portfolio i,
β_i – systematic risk measure referring to the asset/portfolio i,
r_{it} – the return of the asset/portfolio i in time t,
r_{ft} – the return of the risk-free asset/portfolio in time t,
r_{mt} – the return of the market portfolio in time t,

ε_{it} – random component.

Jensen's alpha derived from the SML equation constitutes a difference between the expected return and the return resulting from the CAPM model. Figure 4.3. constitutes a graphic presentation of exemplary cases of Jensen's alpha with the use of SML. The alpha which equals 0 means that the asset/portfolio is correctly priced (portfolio A in Figure 4.3.). A positive alpha indicates that the asset/portfolio is undervalued (portfolio C in Figure 4.3.). A negative alpha indicates that the asset/portfolio is overvalued instead (portfolio B in Figure 4.3.). The value of alpha indicates the absolute value of the mispricing (Dębski, 2014).

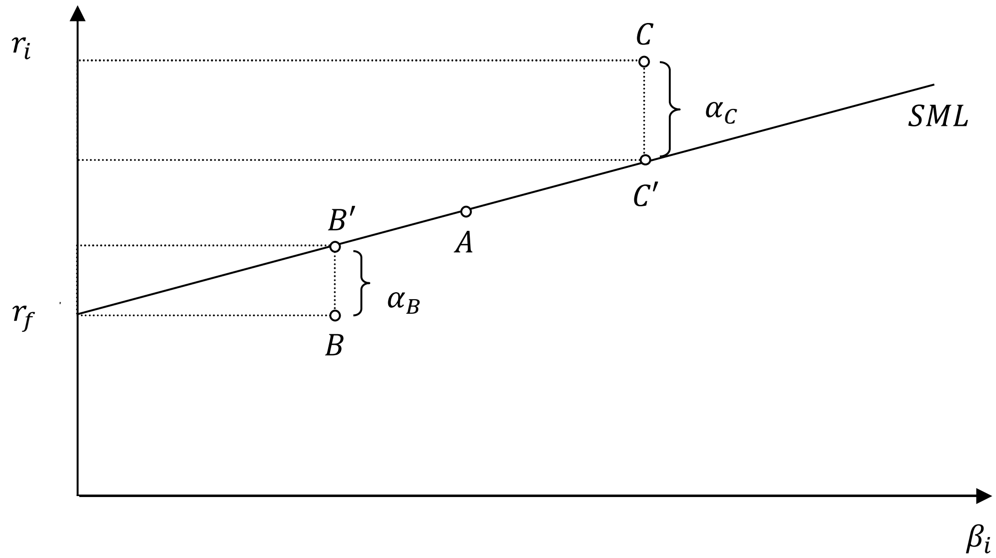

Fig. 4.3. A graphic presentation of exemplary cases of Jensen's alpha with the use of the security market line (SML) of the CAPM model. Source: Author's own study.

As far as testing of market-timing skills is concerned, two classic models of returns, i.e., Treynor-Mazuy (TM) and Henriksson-Merton (MM) models, are widely applied for this purpose. However, they can also be used for the evaluation of the selectivity skills of portfolio managers.

In the first of the aforementioned models, namely, the Treynor-Mazuy model proposed in 1966, a quadratic function superseded a classic linear version of the CAPM model. According to the Treynor-Mazuy model, a quadratic function describes the relation between portfolio and market returns better compared to a linear function due to the reactions of portfolio managers who apply market timing strategies to changing market conditions. Managers correctly anticipating changes in the market conditions decrease the systematic risk exposure of their portfolio in the bear market in order to decrease losses. They also increase the systematic risk exposure of their portfolio in the bull market in order to increase profits.

In the Treynor-Mazuy model, a β parameter from the CAPM model is defined as a linear function of risk premium, which allows to measure the market timing strategy skills. The β parameter is defined as follows:

$$\beta = \gamma_0 + \gamma_p(r_{mt} - r_{ft}). \tag{4.8.}$$

A classic Treynor-Mazuy model is obtained after the application of Formula 4.8. to a classic CAPM model Formula 4.3. It can be formulated as follows:

$$r_{it} - r_{ft} = \alpha_i + \gamma_0(r_{mt} - r_{ft}) + \gamma_i(r_{mt} - r_{ft})^2 + \varepsilon_{it}, \tag{4.9.}$$

where:
α_i – the measure of selectivity skills of a portfolio manager i,
γ_0 – systematic risk measure referring to asset/portfolio i,
γ_i – the measure of the market-timing skills of a portfolio manager i,
ε_{it} – random component that fulfils the assumptions of a classic CAPM.

A positive and statistically significant value of γ_i parameter indicates that a portfolio manager successfully implements a market timing strategy in investment decisions, correctly predicting changes in market conditions and changing the systematic risk exposure accordingly. In addition to the evaluation of the market-timing skills of the portfolio manager, the Treynor-Mazuy model also allows to assess selectivity skills. A positive and statistically significant value of α_i parameter confirms the successful implementation of selectivity skills in investment decisions of a portfolio manager.

The second model mentioned above as a classic model dedicated to the evaluation of market-timing skills of portfolio managers, namely, the Henriksson-Merton model, assumes that the portfolio manager forecasts two states of the market, namely, the bear and bull market, in which two different values of a β parameter are expected. The same as in the case of the classic CAPM model and the Treynor-Mazuy model, a β parameter refers to systematic risk exposure.

A parametric version of the Henriksson-Merton model assumes that the portfolio manager makes forecasts when the market risk premium is positive or negative. Taking into account this assumption, the Henriksson-Merton model introduces to a classic CAPM model a dummy variable D_t that identifies bear and bull market periods. In the bear market conditions, a dummy variable D_t equals 1; however, in the bull market conditions, a dummy variable D_t equals 0, which can be formulated as follows:

$$D_t = \begin{cases} 0, & r_{mt} > r_{ft} \\ 1, & r_{mt} \leq r_{ft} \end{cases}. \tag{4.10.}$$

A classic Henriksson-Merton model in a parametric version can be formulated as follows:

$$r_{it} - r_{ft} = \alpha_i + \beta_i(r_{mt} - r_{ft}) + \gamma_i D_t(r_{mt} - r_{ft}) + \varepsilon_{it}, \tag{4.11.}$$

where:

α_i – the measure of selectivity skills of a portfolio manager i,
β_i – systematic risk measure referring to asset/portfolio i,
γ_i – the measure of market-timing skills of a portfolio manager i,
ε_{it} – random component that fulfils the assumptions of a classic CAPM.

A positive and statistically significant γ_i parameter suggests that a portfolio manager successfully implements a market timing strategy in investment decisions. The same as in the case of the Treynor-Mazuy model, a positive and statistically significant value of α_i parameter confirms the successful implementation of selectivity skills in investment decisions of a portfolio manage (Zamojska, 2012) r.

In addition to some more sophisticated performance analysis (as the ones presented in this section so far), investors sometimes start and unfortunately end their analysis of portfolio performance on the analysis of raw portfolio returns. In this approach, investors derive from returns only some basic characteristics without taking into account their risk (Aldridge, 2010).

One of the most basic measures that allows for the comparison of results generated by portfolio is a total shareholder return (TSR). TSR is a universal measure that can be successfully applied to any type of asset/portfolio. The TSR can be formulated as follows:

$$TSR_T = \frac{p_T - p_0}{p_T}, \tag{4.12.}$$

where:
p_T – participation unit price on realization day T,
p_0 – participation unit price on the beginning day 0.

The TSR is a simple measure that allows to calculate the return in a specific period of investment. It can be compared between different investment variants; nevertheless, it does not consider any risk related to evaluated investment and does not allow for the analysis of dynamics of price changes.

In terms of a mathematical expression, a TSR formula is directly related to a formula of a periodical simple rate of return, which can be expressed as a quotient of profit and price from the previous period. A simple rate of return r_t can be formulated with the following equation (Zamojska, 2012):

$$r_t = \frac{p_t - p_{t-1}}{p_{t-1}}, \tag{4.13.}$$

where:
p_t – participation unit price on day t,
p_0 – participation unit price on day $t-1$.

The simple rate of return can be used to construct a time series of one-period returns that shows the dynamics of price changes and allows for more sophisticated analyses. Nevertheless, due to statistical features of simple returns, the so-called logarithmic returns resulting from a continuous compounding are much more preferable in financial analysis. Logarithmic returns are additive, and thus, their distribution is more similar to a normal one. They are more robust to extreme observations. Moreover, they are not bigger than simple returns. They can be formulated as follows (Niedziółka, 2016):

$$lnr_t = ln\left(\frac{p_t}{p_{t-1}}\right). \tag{4.14.}$$

Due to the beneficial statistical features of logarithmic returns, they were used to create financial time series analysed for the purpose of this study.

4.1.3. The relative measures of portfolio performance

The basic characteristics of returns, such as the average return, standard deviation, skewness, or kurtosis, which can be derived from the time series of portfolio returns, provide an informational value pertaining to the performance and risk of portfolio. However, they do not allow for an easy comparison of performance and risk between different portfolios. Nevertheless, this is possible due to the relative measures of portfolio performance, which allow to compare performance of similar portfolios regardless of differences in risk levels.

Relative performance ratios presented in this section are the cardinal measures which can be later used to construct the ordinal measures, which indicate a position of a portfolio in a ranking of performance of similar portfolios.

Measures based on the CAPM model

To begin with the classic relative measures of portfolio performance, two most famous ones are strictly related to the CAPM model, namely, the Sharpe ratio and the Traynor ratio, proposed by the fathers of the CAPM model, William Sharpe and Jack Treynor.

The Sharpe ratio was proposed by Sharpe (1966) and originally was called the reward-to-variability ratio. However, this name did not seem to catch on, neither among the researchers nor among the practitioners. It equals an average risk premium (excess return) per unit of a total risk measured as a standard deviation of the portfolio returns. The Sharpe ratio can be formulated as follows (Ostrowska, 2014):

$$S_i = \frac{r_i - r_f}{\sigma_i}, \tag{4.15.}$$

where:
r_i – average portfolio return in the period analysed,
r_f – average risk-free asset return in the period analysed,
σ_i – the standard deviation (total risk) of portfolio return in the period analysed.

As a measure strictly related to the CAPM model, the Sharpe ratio constitutes the slope of the capital market line (CML), as depicted in the example in Figure 4.4. The maximisation of the Sharpe ratio is equivalent to maximisation of the slope of the CML. The higher the Sharpe ratio, the better the portfolio performance. All efficient portfolios lying on the CML have the same Sharpe ratio.

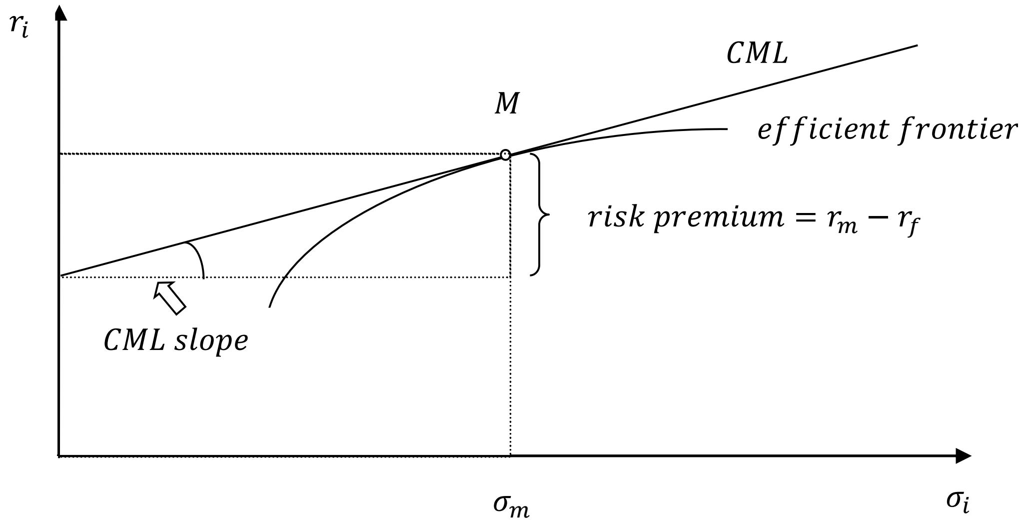

Fig. 4.4. A graphic presentation of an exemplary capital market line (CML) of the CAPM model and the Sharpe ratio. Source: Author's own study.

According to Aldridge (2010), the return from the risk-free assets r_f reflects the opportunity costs as well as the costs of position carrying, which are related to a trading activity. Due to no positions carried overnight in high-frequency trading, the costs of position carrying equal 0. Thus, the Sharpe ratio applicable in the case of the high-frequency trading strategies can be formulated as follows:

$$S_{(HFT)i} = \frac{r_i}{\sigma_i}. \tag{4.16.}$$

The Treynor ratio proposed by Treynor (1965) is the next popular classic relative measure of portfolio performance based on the CAPM model. As opposed to the Sharpe ratio, it is calculated as a risk premium (excess return) per unit of a systematic risk, which is just a part of a total risk used in the Sharpe ratio. The Treynor ratio can be formulated as follows (Perez, 2020):

$$T_i = \frac{r_i - r_f}{\beta_i}, \tag{4.17.}$$

where:
β_i – the systematic risk of portfolio i in the period analysed.

The Treynor ratio is also a slope of the security market line (SML), as shown in the example in Figure 4.5. The maximisation of the Treynor ratio is equivalent to the maximisation of the slope of the SML. The higher the Treynor ratio, the better the portfolio performance. The Treynor ratio is especially dedicated to the measurement and comparison of the performance of portfolios that comprise assets with different systematic risk exposures, which are selected so that the specific risk is diversified. All correctly priced portfolios lying on the SML have the same Treynor ratio.

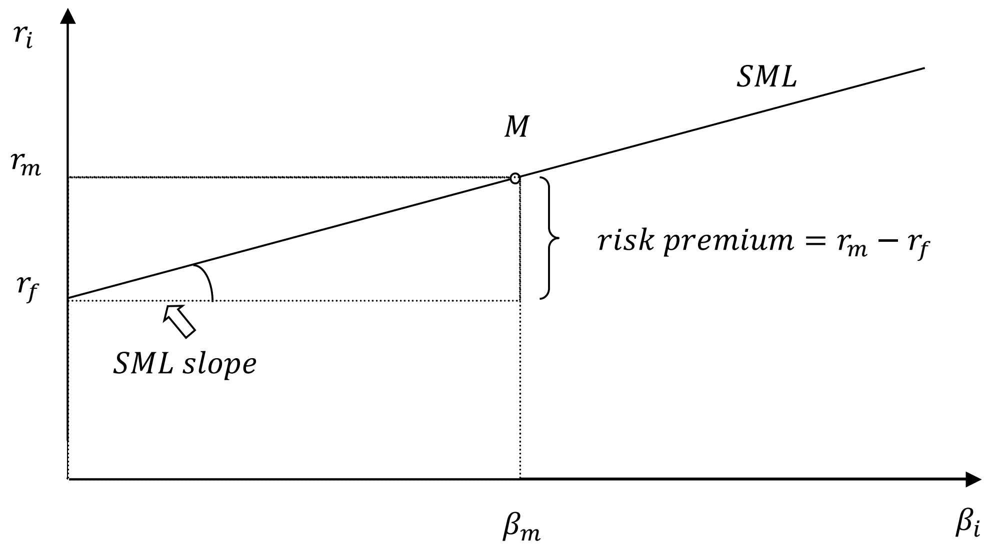

Fig. 4.5. A graphic presentation of an exemplary security market line (SML) of the CAPM model and the Treynor ratio. Source: Author's own study.

Aldridge (2010) did not mention this, however, referring to her line of thinking that pertains to a role of the return from the risk-free assets r_f in the Sharpe ratio, the Treynor ratio, which is applicable in the evaluation of performance of high-frequency trading strategies can be formulated as follows:

$$T_{(HFT)i} = \frac{r_i}{\beta_i}. \tag{4.18.}$$

It is also worth mentioning a relative measure that adjusts not the excess returns as was in the case of the classic CAPM-based measures discussed so far (The Sharpe ratio and the Treynor ratio), but a constant term from asset pricing models, which is treated as a proxy for the selectivity skills of a portfolio manager. According to Treynor and Black (1973), the appraisal ratio, which adjusts the alfa parameter for the specific risk estimated as the standard deviation of standard errors received in the pricing model estimation process, is a correct measure of the selectivity skills of the portfolio manager. Its application is especially justified when two portfolios compared have the same alfa parameter but different specific risk levels. The same alfa parameters may suggest that both portfolio managers compared have the same selectivity skills. However, due to different specific risk levels, the conclusions may be changed. The appraisal ratio can be expressed with the following formula:

$$\text{Appraisal}_i = \frac{\alpha_i}{\hat{\sigma}_i}, \tag{4.19.}$$

where:

α_i – the constant term of asset pricing models that is treated as a proxy for the selectivity skills of the portfolio manager,

$\hat{\sigma}_i$ – specific risk estimated as the standard deviation of standard errors received in the process of the pricing model estimation.

When active portfolio management leads to the diversification of a specific risk, the standard deviation of standard errors received in the pricing model estimation process decreases. Furthermore, when implemented active portfolio management strategies confirm the selectivity skills of portfolio manager, the alpha parameter increases. The appraisal ratio can also be interpreted as a premium for taking the risk of active management.

As the statistical assumptions of a classic CAPM model state that the distribution of portfolio returns has to be normal, the classic relative measures of portfolio performance may underestimate the risk and performance. They may not account for the tail risk and extreme returns, which constitute typical deviations from the normal distribution of financial time series.

According to Zamojska (2012), a lack of normality of distributions may result from strategies applied by managers who usually do not diversify their portfolios and restrict themselves to just few assets. This is strictly related to a central limit theorem, which suggests that even if the returns of particular assets are not normal, the returns of a whole portfolio should be normal. Moreover, some managers apply some derivative instruments, which result in fat tails and asymmetric distribution of returns.

In order to deal with the problem of the tail risk, some adjusted relative measures of performance have been developed. The main changes applied in the adjusted relative measures of performance, compared to the Sharpe and Treynor ratios, consist in the implementation of different risk measures, especially focused on adverse returns. The classic performance measures included both positive and negative returns in the calculation of risk measures. The aforementioned changes were explained by the argument according to which only negative returns are meaningful in the process of estimation and comparison of portfolio performance.

Taking into account risk measures applied, Aldridge (2010) distinguished the three groups of the adjusted relative measures of portfolio performance. According to Aldridge (2010) they can be especially helpful in the evaluation of high-frequency strategy performance:

- measures based on maximum drawdown (MD),
- measures based on lower partial moments (LPMs),
- measures based on value-at-risk (VaR).

Measures based on maximum drawdown (MD)

The first of the abovementioned adjusted performance measures apply risk measures that utilize the maximum drawdown-based methodology, which captures the tail risk. Maximum drawdown constitutes a risk measure that reflects maximum losses, which were historically incurred. This measure reflects the lowest peak-to-through return which was generated from the last global maximum to the minimum, which was observed before the next global maximum. The global maximum is also usually called a high water mark. The lowest return between two successive global maximums (high water marks) is called a drawdown. A maximum drawdown refers to the lowest drawdown in the analysed time series.

The Calmar ratio proposed by Young (1991) modifies a simple Sharpe ratio by replacing the standard deviation of the portfolio with a maximum drawdown. The Calmar ratio can be formulated as follows:

$$Calmar_i = \frac{r_i - r_f}{-MD_i}, \tag{4.20.}$$

where:
MD_i – the maximum drawdown of the returns of portfolio i.

As the Calmar ratio applies a maximum drawdown as a tail risk measure, the Sterling ratio proposed by Kestner (1996) utilizes the average drawdown, which can be formulated with the following equation:

$$Sterling(Kestner)_i = \frac{r_i - r_f}{-\frac{1}{N}\sum_{j=1}^{N} D_{ij}}, \tag{4.21.}$$

where:
D_{ij} – j-th largest drawdown of returns of portfolio i,
N – the number of largest drawdowns taken into account,
j – the number of the largest drawdown.

In the Burke ratio proposed by Burke (1994), a risk premium is divided by the square root of the sum of the square of drawdowns, which can be formulated as follows:

$$Burke_i = \frac{r_i - r_f}{\sqrt{\sum_{j=1}^{N} {D_{ij}}^2}}. \tag{4.22.}$$

The number of drawdowns taken into account can be limited to a specific number of N largest drawdowns.

Also, a modified version of the Burke ratio can often be met in which each drawdown is divided by the number of observations in the entire time series. The modified Burke ratio can be expressed in the following manner (Bacon, 2008):

$$Modified\ Burke_i = \frac{r_i - r_f}{\sqrt{\sum_{j=1}^{N} \frac{{D_{ij}}^2}{n}}}, \tag{4.23.}$$

where:
n – the number of observations in the entire time series.

Measures based on lower partial moments (LPMs)

The next of the above-mentioned groups of the adjusted relative measures of portfolio performance uses lower partial moments (LPMs) of portfolio returns as a risk proxy. The lower partial moments applied in performance measures constitute the regular moments of distribution of adverse returns, i.e., returns that felt below a specific benchmark. The regular moments of the adverse return distribution used in the LPM-based measures are, for instance, the mean, standard deviation, and skewness. As a specific benchmark that defines the upper limit for the returns, for which the moments are calculated, researchers usually choose a minimal acceptable return (MAR) or an investor's return target. When comparing the LPM-based performance measures with the classic ones, a chosen benchmark also replaces the risk-free rate in the numerator.

Shadwick and Keating (2002) as well as Kaplan and Knowles (2004) proposed the Omega ratio, which informs about the excess returns over the benchmark per the average adverse return, i.e., the average of the returns that fall below a specific benchmark. The Omega ratio can be expressed with the following formula:

$$Omega_i = \frac{r_i - \tau}{LPM_{1i}} + 1, \tag{4.24.}$$

where:
τ – the assumed benchmark return, i.e., the minimal acceptable return or the return target of the investor,
LPM_{1i} – the average of the returns that fall below the assumed benchmark return, i.e., the first lower partial moment of the adverse portfolio returns.

The Sortino ratio proposed by Sortino and van der Meer (1991) uses the standard deviation of returns that below a specific benchmark, i.e., the square root of the variance of adverse returns, which constitutes the second lower partial moment of the portfolio returns. The Sortino ratio can be formulated as follows:

$$Sortino_i = \frac{r_i - \tau}{\sqrt{LPM_{2i}}}, \tag{4.25.}$$

where:
LPM_{2i} – the variance of adverse returns i.e., the second lower partial moment of portfolio returns.

Sortino, van der Meer, and Plantinga (1999) proposed the Upside Potential Ratio, which applies the same risk proxy as the Sortino ratio. However, as opposed to the Sortino ratio, it measures the average portfolio return above the selected benchmark per unit of standard deviation of returns that fall below the benchmark. Thus, the main difference in the expression of the ratio is that the Sortino ratio applies the average of all returns in the numerator of the formula, and the Upside Potential Ratio applies the average of just these returns, which are higher than the benchmark. The Upside Potential Ratio can be expressed as follows:

$$\text{Upside Potential}_i = \frac{HPM_{1i}}{\sqrt{LPM_{2i}}}, \tag{4.26.}$$

where:
HPM_{1i} – the average of returns above the assumed benchmark return.

In the Kappa 3 ratio proposed by Kaplan and Knowles (2004), the risk is proxied with the use of the cube root of the third lower partial moment of the portfolio returns. The third lower partial moment reflects the skewness of the adverse returns. The Kappa 3 ratio can be expressed with the following formula:

$$\text{Kappa } 3_i = \frac{r_i - \tau}{\sqrt[3]{LPM_{3i}}}, \tag{4.27.}$$

where:
LPM_{3i} – the third lower partial moment of the portfolio returns.

Measures based on value-at-risk (VaR)

The last of the abovementioned groups of the adjusted relative measures of portfolio performance comprises measures that apply the concept of value at risk as a risk proxy. Two basic ratios from this group use a classic value at risk (VaR) and a conditional value at risk (CVaR).

The value at risk can be defined as a measure that identifies a boundary level of losses for a specified probability of its realization. The conditional value at risk (also often referred to as the expected shortfall) uses a classic value at risk to derive the average of extreme losses that fall beyond the level indicated by the value at risk, i.e., the average of extremely low returns in the tail of returns distribution, which has been indicated by the value at risk.

The classic VaR and CVaR assume the normality of returns. Thus, the application of these risk measures for non-normal returns may lead to severe risk underestimation. Nevertheless, some attempts were made to deal with the problem of VaR application for non-normal returns, like the modified Sharpe ratio proposed by Gregoriou and Gueyie (2003).

The VaR, as a risk proxy, is used in the relative measure of portfolio performance proposed by Dowd (2000), which can be perceived as the excess return per value at risk. It can be expressed as follows:

$$\text{Excess return on VaR}_i = \frac{r_i - \tau}{VaR_i}, \tag{4.28.}$$

where:
VaR_i – the value at risk of returns of portfolio i.

Agarwal and Naik (2004) proposed the conditional Sharpe ratio to replace the VaR with the CVaR as a risk measure. It can be formulated as follows:

$$\text{Conditional Sharpe}_i = \frac{r_i - \tau}{CVaR_i}, \tag{4.29.}$$

where:

$CVaR_i$ – the conditional value at risk of returns of portfolio i.

All the relative measures of portfolio performance presented so far are summarised in Table 4.1.

Group	Author	Formula	Application
Measures based on the classic CAPM model	Sharpe (1966)	$S_i = \frac{r_i - r_f}{\sigma_i}$,	The returns of portfolio are normally distributed
	Treynor (1965)	$T_i = \frac{r_i - r_f}{\beta_i}$,	
	Treynor and Black (1973)	$\text{Appraisal}_i = \frac{\alpha_i}{\hat{\sigma}_i}$,	The returns of portfolio are normally distributed / The evaluation of selectivity skills of the portfolio manager
Measures based on maximum drawdown (MD)	Young (1991)	$Calmar_i = \frac{r_i - r_f}{-MD_i}$,	Suitable for returns that are not normally distributed / Suitable for investors who associate the risk especially with the adverse returns
	Kestner (1996)	$Sterling(Kestner)_i = \frac{r_i - r_f}{-\frac{1}{N}\sum_{j=1}^{N} D_{ij}}$,	
	Burke (1994)	$Burke_i = \frac{r_i - r_f}{\sqrt{\sum_{j=1}^{N} D_{ij}^{2}}}$.	
Measures based on lower partial moments (LPMs)	Shadwick and Keating (2002), Kaplan and Knowles (2004)	$Omega_i = \frac{r_i - \tau}{LPM_{1i}} + 1$,	Suitable for returns that are not normally distributed / Suitable for investors who associate the risk especially with the adverse returns and require a minimal acceptable return in regard to which the risk is defined
	Sortino and van der Meer (1991)	$Sortino_i = \frac{r_i - \tau}{\sqrt{LPM_{2i}}}$,	
	Sortino, van der Meer, and Plantinga (1999)	$\text{Upside Potential}_i = \frac{HPM_{1i}}{\sqrt{LPM_{2i}}}$,	
	Kaplan and Knowles (2004)	$\text{Kappa } 3_i = \frac{r_i - \tau}{\sqrt[3]{LPM_{3i}}}$,	
Measures based on value-at-risk (VaR)	Dowd (2000)	$\text{Excess return on VaR}_i = \frac{r_i - \tau}{VaR_i}$,	The returns of portfolio are normally distributed / Suitable for investors who associate the risk especially with the adverse returns
	Agarwal and Naik (2004)	$\text{Conditional Sharpe}_i = \frac{r_i - \tau}{CVaR_i}$,	

Tab. 4.1. The summary of the relative measures of portfolio performance presented in this section. Source: Author's own study.

Zamojska (2012) suggested that performance ratios that apply a total risk as a correction of returns (for instance, the Sharpe ratio) are suitable for the evaluation of the entire portfolio. A total risk comprises a systematic risk and a specific risk, which can be significantly decreased in a well-diversified portfolio. Therefore, this group of measures is less suitable for the evaluation of performance of portfolio sectors or particular assets. Performance measures that apply systematic risk for the correction of returns, such as the Treynor ratio or Jensen's alpha (although this one is not a relative measure of performance) are suitable for the evaluation of portfolio sectors and particular assets. Measures based on maximum drawdown, lower partial moments, or VaR are suitable for investors who associate risk, especially with the adverse returns. Measures based on maximum drawdown and lower partial moments are suitable for returns marked by asymmetry. Additionally, when an investor requires a minimal acceptable return in regard to which the risk is defined, measures based on lower partial moments are suitable.

The relative measures of portfolio performance allow for a relatively easy comparison of performance between similar funds. Thus, they are used in the process of rankings development. Rankings indicate the order of funds in terms of their performance measured with the use of specific portfolio performance measures. Most willingly applied relative measures of portfolio performance used in the process of rankings development, usually differ just in terms of risk proxy. The position of funds in the rankings affects flows from and to the funds, as rankings constitute a strong factor that affects investors' decisions.

From the point of view of researchers, especially interesting rankings-related topics pertain to a common dependence of rankings developed with the use of different performance measures. Numerous studies conducted in this area mostly suggest that portfolio performance rankings developed with the use of different performance measures are positively and significantly correlated (e.g., Eling & Schuhmacher, 2007; Eling, 2008; Ornelas, Silva, & Fernandes, 2012; Zakamouline, 2010). These results seem to be surprising as different performance measures present various approaches to performance measurement, especially in terms of risk measurement.

4.2. The review of literature related to the evaluation of the performance of quantitative funds

Using a sample of 6,352 live and dead hedge funds over the period from January 1994 to March 2009, retrieved from the Hedge Fund Research (HFR) database, Chincarini (2014) made an attempt to compare the performance of quantitative and qualitative hedge funds. Furthermore, using a self-modified model originally proposed by Fung and Hsieh (2004) Chincarini made and attempt to identify the risk factors of both distinguished groups. Nevertheless, the emphasis was not on the comparison of the exposure to different risk factors, but on the alpha parameters of the models. Furthermore, to identify differences in market timing between the two groups of funds, a Henrikkson-Merton timing variable was added to the aforementioned model. Finally, the researcher tried to compare performance differences between the quantitative and qualitative hedge funds in up and down market periods as well as during the global financial crisis of 2008.

The comparison of basic characteristics of returns and relative measures of portfolio performance, namely, the Sharpe ratio, the Sortino ratio, the Omega ratio, the Calmar ratio, and the Sterling ratio, did not allow to draw any unambiguous conclusions, as results were classification-dependent. In other words, the classification methodology that aimed to distinguish quantitative and qualitative funds led to different results. The same referred to the results of normality tests of returns. To distinguish quantitative and qualitative funds Chincarini (2014) applied two classification methods. They will be discussed in detail in Chapter 5.

The estimates of a self-modified model originally proposed by Fung and Hsieh (2004) suggested that a pooled group of hedge funds had positive alphas. However, quantitative funds outperformed qualitative funds taking into account the alpha parameter. Such results were obtained taking into account the entire research period. However, qualitative hedge funds seemed to perform better during up markets. On the other hand, during down markets, qualitative hedge funds seemed to perform worse. Most of the outperformance of qualitative funds by quantitative funds resulted from down markets. The same models estimated in a predefined period related to the global financial crisis of 2008 suggested that a pooled group of hedge funds had negative alphas. However, in most cases quantitative funds performed better than qualitative funds. When it comes to market-timing skills testing, quantitative funds in most cases turned out to be better.

Harvey et al. (2017) made an attempt to compare the performance of systematic and discretionary hedge funds (as they called them) by analysing a sample of 6955 equity hedge funds and 2182 macro hedge funds over the period 1996-2014. The sample was retrieved from the Hedge Fund Research (HFR) database. The comparison of the performance of systematic and discretionary hedge funds was performed especially with the use of alpha parameter derived from the estimated model. For the purpose of the model estimation, the researchers formed indexes for each fund category, i.e., they averaged returns across funds of a particular category. The estimated model comprised three types of performance factors namely, traditional, dynamic, and volatility factors. Traditional factors included three asset classes, i.e., equities, bonds, and credit. A group of dynamic factors comprised three Fama-French US stock factors (size, value, and momentum), as well as the FX carry factor. A volatility factor included in the model was a one-month-long at-the-money S&P 500 straddle, bought at month end and held to expiry. Harvey et al. (2017) also examined correlations between the unadjusted and risk-adjusted returns of two groups in order to verify whether the two strategies were similar. In addition, the researchers examined the percentiles of various performance measures in order to compare the homogeneity of the two groups. In the case of the examination of percentiles, the researchers took into account such performance measures as unadjusted returns, the Sharpe ratio, alpha, and appraisal ratio. This time, they were calculated at the level of each fund.

The results of the study by Harvey et al. (2017) suggest that in the group of equity hedge funds, discretionary managers outperformed systematic managers in terms of raw returns. However, after adjusting them for risk, systematic managers slightly outperformed discretionary ones. In the group of macro hedge funds, systematic managers outperformed discretionary managers taking into account both the raw returns and the risk-adjusted returns. Regarding factor attribution, the exposure to risk factors was higher in the case of discretionary managers. When it comes to the results of the study on correlations between the unadjusted and risk-adjusted returns of the two groups, high and positive correlation coefficients suggested that discretionary and systematic strategies were similar. This conclusion can be additionally confirmed by the results of the analysis of percentiles according to which discretionary and systematic strategies were similarly homogenous in terms of performance generated.

In one of the first studies dedicated to the comparison of the performance of quantitative and qualitative funds, Parvez and Sudhir (2005) used a relatively small sample compared to the other studies discussed in this section. They retrieved a sample of 30 enhanced index equity mutual funds from the Morningstar on Disc database in the period from January 1980 to December 2000 and divided it into two groups, namely a group of 23 fundamental funds and a group of 7 quantitative funds (as they called them). Additionally, 22 other quantitative equity mutual funds were included in the research sample. The researchers measured the performance of the analysed funds using some basic characteristics of returns, namely, the Sharpe ratio, appraisal ratio, tracking error, and alpha coefficients from the classic CAPM model and Fama–French three-factor model. They also applied a modified Fama–French three-factor model with additional momentum factor.

Referring to the aforementioned small sample size, Parvez and Sudhir (2005) mentioned that the results of their study must be interpreted with caution, as a small sample size may result in a limited power of tests. As opposed to non-quantitative enhanced index funds (a sample of 23 funds), quantitative funds (a sample of 7 funds) managed to complete their statutory task, i.e., they managed to outperform their benchmarks. The results obtained for all examined enhanced index funds suggested that the funds did not outperform their benchmark. Surprisingly, all examined enhanced index funds turned out to outperform their benchmark after the addition of the momentum factor to the Fama–French three-factor model. Regarding a sample of 22 quantitative equity mutual funds, this sample was divided into four sub-samples in terms of stocks they invested in (large cap growth, large cap value, small cap growth, small cap value). The results suggest that only small cap growth funds had significant positive alphas.

Similarly to Chincarini (2014) and Harvey et al. (2017), Chuang and Kuan (2018) retrieved their research sample from the Hedge Fund Research (HFR) database. They aimed to compare the performance of systematic and discretionary hedge funds (as they called them). They focused on four sub-strategies of equity hedge strategy i.e., equity market neutral, quantitative directional, fundamental growth, and fundamental value. Additionally, they decided to include in the sample two sub-strategies from the macro strategy, i.e., systematic diversified and discretionary thematic. The sample consisted of 2,149 equity hedge funds and 603 macro hedge funds. The monthly returns of funds in the period from January 1996 to November 2015 constituted a basis for the calculations. The researchers compared performance between the groups with the use of some basic return characteristics, the Sharpe ratio and alpha. The alpha they estimated came from 5 different models, namely, the CAPM model, the Fama-

French 3-factor model, the Fung and Hsieh 5-factor model, the Fung and Hsieh 7-factor model, and the 11-factor model by Bali (2014; cited in Chuang and Kuan, 2018).

The results received suggest that in the majority of cases, systematic funds tended to do better in terms of both the raw returns and risk-adjusted returns. The average alphas of both systematic and discretionary funds turned out to be positive. In addition, to verify whether performance was a result of the authentic skills of managers, rather than their luck, the researchers applied a bootstrap analysis of factor-adjusted returns of both systematic and discretionary funds. The obtained results suggested that in the case of both compared groups, performance was due to the authentic skills of their managers. Moreover, the authors conducted a stochastic dominance test to compare the performance of both systematic and discretionary funds. The standardized alphas of systematic funds turned out to stochastically dominate the standardized alphas of discretionary funds in the group of equity hedge funds. In the case of macro hedge funds such conclusions did not hold.

Abis (2018) made an attempt to examine differences in investment style and performance between quantitative and systematic US equity mutual funds in the period December 1999-December 2015. Research sample consisted of 2,607 funds divided into two groups, i.e., 599 quantitative funds and 1,851 discretionary funds. The sample was retrieved from the CRSP Mutual Fund dataset. The researcher applied the model by Kacperczyk, Van Nieuwerburgh, and Veldkamp (2016; cited in Abis, 2018). The results of the study suggest that quantitative funds specialize in stock picking whereas discretionary funds alternate between market timing and stock picking. Quantitative funds hold more stocks. They also display pro-cyclical performance whereas discretionary funds display counter-cyclical performance. Discretionary funds generate slightly greater risk-adjusted returns than quants during recessions. However, quantitative funds have better risk management and portfolio diversification throughout the business cycle. The trades of quantitative funds are vulnerable to overcrowding defined by the author as the combination of commonality in portfolios of quantitative funds and their prevalence in the market. In addition, discretionary funds focus on stocks for which less overall information is available. Discretionary funds use this approach to reduce the information gap with regard to quantitative funds, which have a greater information processing capacity. However, strategies of quantitative funds seem to be less flexible.

4.3. Conclusions

The theory presented in this chapter constitutes a background for developing the research methodology for the needs of the study on performance of quantitative funds. This study aims to verify hypotheses H1 and H3. The main research hypothesis H1 states that the performance of quantitative funds is higher than performance of qualitative funds. The supplementary research hypothesis H3 states that quantitative funds perform better than qualitative funds in periods of a low weak-form informational efficiency of equity markets. In addition, the methodology of portfolio performance evaluation, which was developed based on the knowledge presented in this chapter, allows to answer supplementary research questions posed in the introduction. The review of literature, which was conducted in this chapter, provided some reference points related to methodology applied and results obtained in issue-related studies, which can be addressed in further discussion.

This chapter presented an idea of portfolio performance evaluation and focused especially on one of its areas, namely performance measurement. The literature mainly distinguishes two widely used groups of portfolio performance measures, namely, the absolute measures of portfolio performance and the relative measures of portfolio performance. The measures discussed in this chapter focussed on selectivity and market-timing skills of portfolio managers. Many popular and widely applied portfolio performance measures come from asset pricing models, which were presented in this chapter. This chapter introduced the CAPM model, its adjustments, and some further theoretical considerations, which had their roots in this model. A significant part of this chapter was dedicated to the relative measures of portfolio performance, which were divided into four groups, namely, measures based on the CAPM model, measures based maximum drawdown, measures based on lower partial moments, and based on value-at-risk. This division is well known in the issue-related literature.

5. The characteristics of the research sample and research methodology

The presentation of the research methodology developed for the needs of the study on the weak-form efficiency and performance of quant funds constitutes a primary objective of this chapter. Nevertheless, this chapter also presents a methodology for collecting research sample and a methodology for classifying investment funds as quantitative or qualitative, which constitutes a fundamental problem in the light of missing classifications in financial databases.

The study conducted for the needs of this thesis began with the examination of the weak-form efficiency of quantitative funds. The research methodology pertaining to the verification of the hypothesis referring to the character of returns of quant funds in the context of the weak-form informational efficiency was based on well-known methods, willingly applied in the issue-related studies, which were discussed in Chapter 3. However, to the best of author's knowledge, there is a lack of studies on the weak-form efficiency of investment funds directly related to quantitative funds. A study conducted for the needs of this thesis had a comparative character, in which the results of the quantitative funds were mostly compared to the results of the qualitative funds and a relevant equity market benchmark. The hypothesis referring to the features of returns of quant funds in the context of the weak-form informational efficiency was formulated as follows:

H2: The weak-form informational efficiency of quantitative funds is higher than the weak-form informational efficiency of qualitative funds.

Similarly as in the case of the study on the weak-form efficiency of quantitative funds, the methodology dedicated to the study on the performance quantitative funds was based on methods commonly applied in issue-related studies, also related to quantitative funds. They were discussed in Chapter 4. Furthermore, similarly as in the case of the study on the weak-form informational efficiency of quantitative funds, the performance study of quant funds had a comparative character. The research hypotheses verified in the study on the performance of quant funds were formulated as follows:

H1: The performance of quantitative funds is higher than the performance of qualitative funds.

H3: Quantitative funds perform better than qualitative funds in periods of low weak-form informational efficiency of equity markets.

The majority of financial databases do not provide any classification that indicates whether investment funds are quantitative or qualitative. Due to this problem, the classification of funds in issue-related studies usually had to be performed individually by researchers. This problem was also encountered in this study. The importance of the aforementioned fund classification is high, as an inaccurate split of funds may lead to incorrect conclusions regarding the differences between the groups compared.

Section 5.1. presents approaches to distinguishing quantitative and qualitative funds in issue-related studies in the face of no issue-relevant fund classification in financial databases. Some of discussed approaches constituted a basis for dealing with the problem of a lacking issue-relevant fund classification in this study. The research sample collected for the needs of this study, as well as the method of division of funds into quantitative and qualitative groups, is presented in Section 5.2. The research methodology developed for the needs of the study on the weak-form efficiency and performance of quantitative funds is presented in Section 5.3.

5.1. Approaches to quant funds sample collecting in the prior issue-related studies

Most financial databases do not provide any classification that indicates whether a fund is quantitative or qualitative. This is understandable, at least partially, as there has been no complete consensus made regarding the definitions of these two categories. In many cases, it would be difficult to classify funds unambiguously, although this problem could be solved for instance, by introducing categories that indicate the application of some mixed approaches to the investment process. Despite the lack of problem-relevant classification, some researchers made an attempt to deal with this problem on their own. This section discusses some approaches to distinguishing the sub-samples of investment funds applied in the previous issue-related studies. Some of the approaches discussed constituted a basis for developing a methodology of fund classification for the needs of this thesis, which is described in Section 5.2.

A study by Parvez and Sudhir (2005) was probably the first one, which made an attempt to deal with the problem of a missing fund classification in the applied database, indicating whether an investment process of a fund is based on quantitative techniques. They focused only on enhanced index equity funds. A list of such funds was retrieved from the Morningstar on Disc database. To make sure that the research sample includes only enhanced index equity funds, the researchers examined fund objectives and investment processes described in fund prospectuses. A fund was included in the research sample only if it claimed to follow an enhanced index strategy and described it. With the use of information included in prospectuses, the researchers bifurcated a sample of 30 enhanced index equity funds into a sub-sample of 23 fundamental funds and a sub-sample of 7 quantitative funds.

The researchers also examined an additional sample consisting of 22 quantitative funds. This sample was examined separately. It came from a list of the already-classified quantitative funds in the Morningstar on Disc database. Additionally, it was supplemented with the other quant funds found in the publications in Lexis-Nexis. Moreover, the researchers examined the prospectuses of all funds to confirm whether the they actually followed a quantitative portfolio management process.

The study by Parvez and Sudhir (2005) covered the period from January 1980 to December 2000. Sub-samples were distinguished on the basis of an in-depth analysis of prospectuses. This approach would be difficult to apply in the case of larger samples. Thus, further issue-related studies discussed in this section implemented approaches that aimed to find more efficient ways to split more numerous samples. Some of them also aimed to develop method, which would be less and less researcher-subjective.

Keeping in mind that most of the hedge funds are neither strictly quantitative or qualitative, Chincarini (2014) made an attempt to distinguish two groups of hedge funds, namely quantitative and qualitative hedge funds. Hedge funds divided into two aforementioned groups came from a sample of 10,007 live and dead hedge funds, available in the Hedge Fund Research (HFR) database as of June 2009. The study by Chincarini (2014) covered the period from January 1994 to March 2009. The number of 10,007 excluded funds-of-funds, which were not considered in the study. The study assumed to analyse monthly returns; hence, 139 funds that did not report on monthly basis were dropped. Another 3,516 funds were dropped due not fulfilling the requirement of having at least 36 consecutive months of data. After exclusions, a final sample consisted of 6,352 hedge funds, which were then classified as quantitative or qualitative ones. To separate quantitative and qualitative funds two classification methods were used:

- classification 1 – the samples of quantitative and qualitative funds were separated on the basis of HFR category names and/or descriptions. The main method applied to classify each fund group was to look for terms like *quantitative* and *systematic* or a description of a similar nature to place a fund group in the quantitative category. On the other hand, in the case of the presence of a word like *discretionary*, the fund group was considered a qualitative one.
- classification 2 - the samples of quantitative and qualitative funds were separated on the basis of the search for word in the HFR strategy description of each fund. The HFR strategy description was analysed in terms of the appearance of particular words. A fund was classified as a quantitative one, when in its strategy description one of the following words appeared: *automate, statistic, econometric, algorithm, model, mathematical, or quantitative*, and the word *qualitative* did not appear. When the word *qualitative* appeared in the fund strategy description, a fund was classified as a qualitative one. A fund was also classified as a qualitative one, when none of the 'quantitative' words appeared in the fund strategy description.

Classification 2 was applied to check the results against the first method of separating quantitative and qualitative hedge funds. Using classification 1, due to incomprehensive descriptions, Chincarini (2014) managed to categorise only 2 out of four main HFR categories, and 10 sub-categories out of 18 available. The structure of the distinguished groups is presented in Table 5.1.

		Quantitative		Qualitative	
		HFR sub-category	Count	HFR sub-category	Count
HFR category	Equity Hedge	Equity Market Neutral	472	Fundamental Growth	775
		Quantitative Directional	296	Fundamental Value	1337
	Macro	Commodity Systematic	71	Commodity Discretionary	18
		Currency Systematic	161	Currency Discretionary	19
		Systematic Diversified	588	Discretionary Thematic	287
		Total	1588	Total	2436

Tab. 5.1. The structure of the research samples distinguished by Chincarini (2014) based on classification 1. Source: Author's own study based on Chincarini (2014)

Using classification 2, the samples of 1,040 quantitative and 5,248 qualitative hedge funds were distinguished. The structures of these two groups, including their division into the HFR categories and sub-categories, were not provided by Chincarini (2014).

The object of the study by Chincarini (2014), i.e., quantitative and qualitative funds, as well as their separation methodology, were criticised by Harvey et al. (2017), who made an attempt to measure the performance of the so-called systematic and discretionary hedge funds. Their research sample was based on data also retrieved from the HFR database and covered the period 1996–2014. The same as Chincarini (2014), they focused only on 2 largest HFT categories, i.e., Equity Hedge and Macro. After excluding funds that reported less frequently than monthly and that did not have at least 36 consecutive monthly data on net asset value, as well as after dropping sub-categories referred to as 'multi-strategy', the final research sample consisted of 6,955 Equity Hedge funds and 2,182 Macro funds. Unlike Chincarini (2014), whose word-picking method was highly subjective, Harvey et al. (2017) followed a more formal method for picking the words that could be used for separating systematic and discretionary hedge funds. Utilizing the HFR-provided split into systematic and discretionary macro funds as a learning set (Systematic Diversified and Discretionary Thematic) and applying some formal criteria, the researchers arrived at the following classification rule:

- a hedge fund was classified as systematic, when in a fund description one of the following words appeared: *system, statistical, model, computer, approx, algorithm*,
- a hedge fund was classified as discretionary, when none of the aforementioned systematic words appeared in the fund description.

The aforementioned rule was applied to all hedge funds included in the study. Table 5.2. presents the structure of the research samples distinguished by Harvey et al. (2017) using their own classification rules and the classification rules proposed by Chincarini (2014).

Specification \ Methodology		Harvey et al. (2017)				Chincarini (2014)				Total	
HFR categories \ Classification		Systematic		Discretionary		Systematic		Discretionary			
HFR category	HFR sub-category	Count	%	Count	%	Count	%	Count	%	Count sub-cat.	Count cat.
Equity Hedge	Equity Market Neutral	562	48.8%	590	51.2%	529	45.9%	623	54.1%	1152	6955
	Quantitative Directional	282	40.9%	407	59.1%	292	42.4%	397	57.6%	689	
	Fundamental Growth	292	14.0%	1792	86.0%	235	11.3%	1849	88.7%	2084	
	Fundamental Value	539	17.8%	2491	82.2%	500	16.5%	2530	83.5%	3030	
Macro	Systematic Diversified	985	68.4%	455	31.6%	687	47.7%	753	52.3%	1440	2182
	Discretionary Thematic	134	18.1%	608	81.9%	137	18.5%	605	81.5%	742	

Tab. 5.2. The structure of the research samples distinguished by Harvey et al. (2017) using classification rules proposed by Harvey et al. (2017) and Chincarini (2014). Source: Author's own study based on Harvey et al. (2017)

Table 5.3. presents words that appear in the classification rules only in the study by Harvey et al. (2017) and only in the study by Chincarini (2014), as well as words that appear in both studies. If any of these words appeared in the fund description, a fund was classified as systematic by Harvey et al. (2017) and quantitative by Chincarini (2014). The results of such a classification are presented in the previous table, i.e., Table 5.2.

Harvey et al. (2017)	Common	Chincarini (2014)
approx	algorithm	automate
computer	model	econometric
system	statistical	mathematical
		quantitative

Tab. 5.3. The words that appear in the classification rules only in the study by Harvey et al. (2017) and only in the study by Chincarini (2014), as well as words that appear in both studies. Source: Author's own study based on Harvey et al. (2017)

None of the words used by Chincarini (2014) only (a column on the very right in Table 5.3.) met all formal criteria of Harvey et al. (2017). Despite this fact, the application of both classification rules brought not so divergent results when it comes to separating systematic funds from discretionary ones in the sample of Harvey et al. (2017) (see Table 5.2.) , at least in terms of their count. The biggest difference appears for the split of Macro Systematic Diversified, where the classification of Harvey et al. (2017) returned 68.4% of systematic funds and the classification of Chincarini (2014) only 47.7%. It is also worth mentioning about one more difference between the classification rules of Harvey et al. (2017) and Chincarini (2014), which was not mentioned by Harvey et al. (2017). Namely, Harvey et al. (2017) do not mention whether they took into account that Chincarini (2014) classified a fund as qualitative one when the word *qualitative* appeared in the fund description. It is unknown whether Harvey et al. (2017) took this rule into account in their comparison study. This classification rule may be especially important in the case of appearing of both 'quantitative/systematic words' and the word *qualitative* in the fund description.

Abis (2018) made an attempt to divide a sample of 2,607 US equity mutual funds featured in the CRSP Mutual Fund dataset into two groups, namely, the group of quantitative funds and the group of discretionary funds (as she called them). In order to do this, she collected the prospectuses of funds from the Securities Exchange Commission (SEC) and manually categorized a sub-sample of 200 funds, which then was used as a training sample for a number of machine learning algorithms, which categorized a remaining part of funds. The researcher wanted to focus on diversified active US equity mutual funds, and thus international funds, sector funds, unbalanced funds, index funds, and underlying variable annuities were excluded. Abis (2018) also excluded funds with less than 5 million USD assets under management or devoting less than 80% of their portfolios to standard equities or holding fewer than 10 stocks. The beginning of the research period resulted from the mandatory disclosure that had to appear in the fund prospectuses starting from December 1999. The aforementioned mandatory disclosure referred to the principal investment strategies and explanation on the buy and sell decision process of the fund adviser. It was used by the researcher and the machine learning algorithm to categorize a fund as quantitative or discretionary. The study covered the period from December 1999 to December 2015.

The separation of funds began with a manual classification of the subsample of 200 funds using criteria such as the appearance of the word *quantitative* or *systematic* in the fund name or the identification of a fund in media as quantitative or discretionary. In the next step, the researcher pre-processed the aforementioned mandatory disclosure that appeared in the fund prospectus by employing the 'bag of words' approach in order to transform the text into a matrix suitable for automatic processing. The rows of this matrix represented funds, and columns indicated features, which referred to the stemmed words and two-word combinations. Then, in order to train different machine learning algorithms, the researcher used nested cross-validation on 170 manually pre-classified funds. The random forest with an ensemble of 1,000 trees and an entropy-based impurity measure was chosen as the most accurate and transparent algorithm. An estimated random forest model was run for the remaining 30 pre-classified funds obtaining an accuracy of 93.4%. Then the model was used to classify the entire sample. As a result, a sample of 2,607 US equity mutual funds was divided into sub-samples of 599 quantitative and 1,851 discretionary funds. 157 were dropped due to the inaccessibility of prospectuses. The machine learning algorithm used 828 features; however, 10 of them accounted for 21% of the informativeness with respect to reducing classification impurity. Among these first 10 features were such words/words combinations as: *quantit, propertiari, model, base, return, quantit model, use quantit, foreign, process, momentum*. After separating the sub-samples of quantitative and discretionary funds, the researcher conducted a search for words in the classified fund prospectuses. The researcher looked for some phrases from the following categories: active trading, frequent trading, short sell, trend following. The results of this search (also presented in Table 5.4.) showed that the prospectuses of quantitative funds more often referred to active trading, frequent trading, short selling, and trend following compared to the prospectuses of discretionary funds.

Word category \ Rate of appearance	Quantitative	Discretionary
Active trading	8.5%	3.8%
Frequent trading	6.8%	3.8%
Short sell	9.0%	3.8%
Trend following	30.3%	5.0%

Tab. 5.4. The rate of appearance of particular word categories in the classified fund prospectuses in the study by Abis (2018). Source: Author's own study based on Abis (2018)

Chuang and Kuan (2018) aimed to obtain as much objectivity as possible when bifurcating their research sample of hedge funds into systematic and discretionary sub-samples (as they called them). Similarly to Abis (2018), they made an attempt split the research sample into two groups with the use of machine learning algorithms. Using the HFR database, they followed Hervey et al. (2017) and focused only on the hedge funds from some of the sub-categories of the Equity Hedge category (Equity Market Neutral, Quantitative Directional, Fundamental Growth, Fundamental Value) and some of the sub-categories of the Macro category (Systematic Diversified, Discretionary Thematic). Both Macro sub-categories were used as the training samples for the machine learning algorithms, which aimed to separate systematic and discretionary funds. The researchers gathered a total of 9,408 fund strategy descriptions as the objects of the analysis, of which 2,234 were classified as Macro and 7,174 as Equity Hedge. The study covered the period from January 1996 to November 2015. The accuracy ratio estimated with the use of a 10-fold cross-validation, measuring the correctness of fund classification, indicated that the random forest classifier yielded the highest average accuracy ratio. Thus, the researchers decided to use this machine learning algorithm to divide a whole sample. Among the most informative features were such phrases as: *global macro, emerg market, fix incom, absolut return, invest process.* They significantly diverged from phrases proposed by Abis (2018).

In order to deal with the issue of missing problem-relevant fund classification in the database used in this study, it was decided to apply a method of the sample split based on the one proposed by Harvey et al. (2017). As a proven method developed with the use of some formal criteria that aimed to improve a method proposed by Chincarini (2014), it should ensure a reliable division of a sample into quantitative and qualitative funds.

5.2. Research sample

For the purpose of this study, data pertaining to investment funds were retrieved from the Thomson Reuters Eikon database. The research sample includes all live and dead funds as of 15/01/2021 that were classified as absolute return funds, equity funds, hedge funds, and mixed asset funds according to the Lipper Global Classification (LGC) scheme by Refinitiv. According to Refinitiv (2019), the purpose of developing this classification was to create homogeneous groups of investment funds with investment objectives that were comparable. The key attributes considered in the process of distinguishing the main classification groups were the type of major asset held by a given fund and its strategy. The Lipper Global Classification provided the following main classification groups: equity, bond, commodities, money market, real estate, mixed asset, hedge, absolute return, alternative, and other. After meeting some additional conditions, investment funds could be also classified into more detailed groups taking into account such attributes as geographic focus, sector focus, currency, risk degree (in the case of mixed asset funds), and strategy (in the case of hedge, absolute return, and other funds). The Lipper Global Classification scheme was applied to funds included in the Thomson Reuters Eikon datasets of mutual funds, hedge funds, insurance and pension funds, closed-end funds, and investment trusts, as well as exchange-traded funds. Not all funds included in the Thomson Reuters Eikon database were classified according to Lipper Global Classification. However, each fund that was classified according to Lipper Global Classification was classified into only one classification group. The Lipper Global Classification is especially focused on the major assets held by a given fund and its strategy rather than on its organisational form.

The study conducted for the needs of this thesis focused on selected four main groups of funds distinguished by the Lipper Global Classification, i.e., equity funds, mixed asset funds, hedge funds, and absolute return funds. Due to the comparative character of the study, the results will also be compared between these groups. However, this study did not consider a more detailed classification within the main groups distinguished by the Lipper Global Classification. One of the reasons for this is that not all sub-groups withing the main classification groups were comparable. For instance, equity funds were additionally divided taking into account geographic focus and sector focus, whereas hedge funds were additionally divided in terms of detailed strategy. What is more, not all funds within the main category were classified into a more detailed category, as they did not meet additional criteria. Some of the sub-groups would also be too less numerous to draw any reasonable conclusions based on their results.

The Lipper Global Classification defines equity funds as funds investing mainly in equities, with ancillary liquid assets such as cash. Mixed asset funds are defined as funds strategically investing in a mix of equity securities and fixed income. Hedge funds are considered unregulated vehicles that generate returns from a derivative hedge-like strategy. They may also employ traditional assets, but only as a means to an end. Absolute return funds are defined as highly regulated funds that mainly operate in the form of mutual, insurance, and pension funds. They use derivatives, and their objective is to generate positive returns regardless of market conditions. In most cases, absolute return funds aim to outperform a risk-free or a cash benchmark and they are not benchmarked against a traditional equity market index.

From a total number of 392 089 retrieved investment funds, 84 899 had to be dropped due to the lack of information pertaining to a country of a primary investment focus. This information refers to a country in which a given investment fund allocates most of its assets. It was needed for the purpose of a regional comparative analysis. It was also needed for the applied performance measures and econometric models in which some country-specific variables like risk-free rate and equity market benchmark returns had to be included. Due to a large number of countries that constituted a country of a primary investment focus and in order to make the regional comparative analysis easier, investment funds with a country of a primary investment focus that had less than 500 investment funds (less than 500 investment funds that indicated this country as a country of a primary investment focus) have been dropped from the sample. Due to this, 7 571 funds have been dropped. In the case of the remaining 299 619 funds, 28 different countries have been indicated as a country of a primary investment focus. Again, due to a large number of countries and in order to make the regional comparative analysis easier, investment funds have been grouped using The United Nations geo-scheme. As a result, 13 regions have been received. Another 4 531 funds had to be dropped due to the lack of investment objective description, which was necessary for further classification as qualitative or quantitative fund. The investment objective description was the only text description of investment fund operations that could contain information allowing to classify it as quantitative or qualitative.

The remaining 295 088 funds do not constitute a final research sample as, ultimately, the final research samples will be selected at three specific stages of the study. These stages will be described in the following sections of this chapter. In the aforementioned stages of the study, different performance measures and econometric models will be estimated for specific rolling windows in the entire time period from 01/01/2000 to 31/12/2020. A given fund will be qualified to a final research sample if it meets a condition of a sufficient number of observations in a window. Thus, a sample of remaining 295 088 funds should be perceived as a basic sample from which the funds will be qualified to the following stages of the study only if they meet the conditions of a required number of observations in a window.

Fund count and percentage share in a basic sample of 295 088 funds with a division into four main strategies according to the Lipper Global Classification scheme are presented in Figure 5.1.

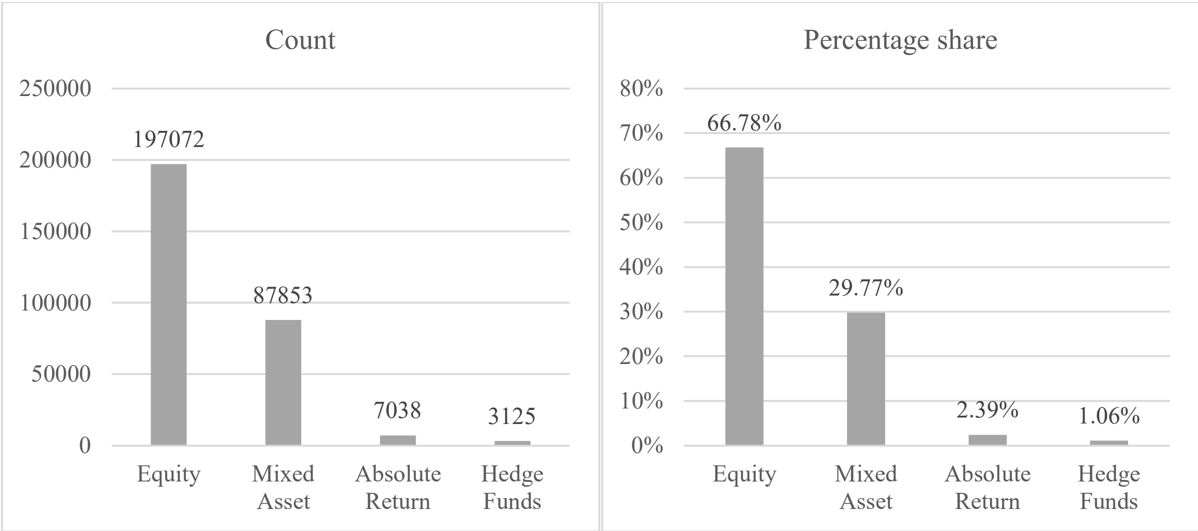

Fig. 5.1. Fund count and percentage share in a basic sample of 295 088 funds with a division into four main strategies according to the LGC scheme. Source: Author's own study

According to Figure 5.1., equity funds constitute the majority of the basic sample, accounting for almost 67% of all funds. Mixed asset funds account for nearly 30% of the basic sample. Absolute return and hedge funds constitute a minority in the basic sample accounting for just 2.39% and 1.06%, respectively.

In the case of the issue-related studies by Chincarini (2014), Harvey et al. (2017), and Chuang and Kuan (2018) hedge funds from the HFR database constituted the only object of the study. In this study, hedge funds are just a small fraction of a basic sample. However, a basic sample of hedge funds in this study is less numerous compared to samples from the aforementioned studies. Regarding other issue-related studies, Abis (2018) focused only on US equity mutual funds. In the case of this study, equity funds are not the only group of funds examined; however, they constitute the majority. This group is also much more numerous compared to the one in the study by Abis (2018).

Figure 5.2. presents fund count and percentage share in a basic sample of 295 088 funds divided into 13 regions according to The United Nations geo-scheme in terms of the region of a primary investment focus.

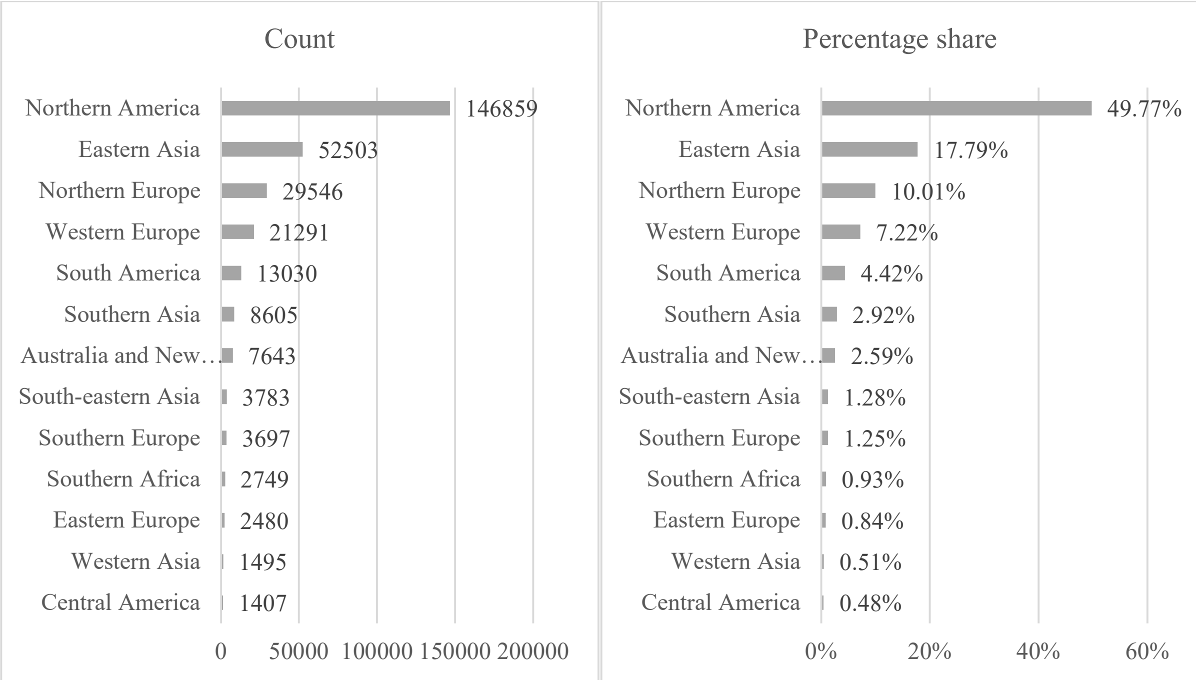

Fig. 5.2. A division of the basic sample of 295 088 funds into 13 regions according to The United Nations geo-scheme in terms of a primary region of investment focus. Source: Author's own study

Referring to Figure 5.2., funds primarily investing in the region of Northern America constitute the largest group, accounting for about 50% of the basic sample. The second largest group of funds in terms of the region of a primary investment focus, namely, Eastern Asia, consists of over 52 thousand funds, accounting for nearly 18% of the basic sample. The groups of funds primarily investing in Northern Europe and Western Europe account for about 10% and 7% of the basic sample, respectively. Other regions are responsible for less than 5% of the basic sample each. In the regional comparison of results pertaining to the study on the weak-form efficiency and performance of quantitative funds, only the first four most numerous groups will be taken into account, namely, Northern America, Eastern Asia, Northern Europe, and Western Europe. The first four most numerous groups distinguished in terms of the region of a primary investment focus account for about 85% of investment funds included in the basic research sample.

A division of the basic sample of 295 088 funds into 13 regions according to The United Nations geo-scheme in terms of the region of a primary investment focus and four main strategies according to Lipper Global Classification scheme is presented in Table 5.5.

Strategy / Region	Equity	Mixed Asset	Absolute Return	Hedge Funds	Total
Northern America	100620	41443	3429	1367	**146859**
Eastern Asia	39480	12310	221	492	**52503**
Northern Europe	19504	8892	896	254	**29546**
Western Europe	14459	5317	1464	51	**21291**
South America	3711	8878	5	436	**13030**
Southern Asia	5230	3223	15	137	**8605**
Australia and New Zealand	5621	1756	132	134	**7643**

South-eastern Asia	2675	1061	37	10	**3783**
Southern Europe	1314	1697	634	52	**3697**
Southern Africa	1183	1346	83	137	**2749**
Eastern Europe	1955	459	13	53	**2480**
Western Asia	653	839	1	2	**1495**
Central America	667	632	108	0	**1407**
Total	**197072**	**87853**	**7038**	**3125**	**295088**

Tab. 5.5. A division of the basic sample of 295 088 funds into 13 regions according to The United Nations geo-scheme in terms of the region of a primary investment focus and four main strategies according to the LGC scheme. Source: Author's own study

The regions of a primary investment focus (rows) in Table 5.5. are sorted in descending order taking into account the total count of funds in each region (last column). The order of the regions is in line with the one in Figure 5.2. It is worth mentioning that this order would not be the same if the regions were sorted taking into account any of four strategies separately. Despite this fact, the total fund count (the last column) was used in order to choose four most numerous regions for the needs of the regional comparison of results pertaining to the study on the weak-form efficiency and performance of quantitative funds. Strategies (columns) are also sorted in descending order taking into account the total count of funds in each strategy group (last row). This order is in line with the one in Figure 5.1.

Table 5.5. shows that the research sample applied in this study is marked by a relatively large fund count and diversity of the analysed strategies and regions of a primary investment focus compared to the other issue-related studies discussed in Section 5.1. It is worth noting that all regions are imbalanced in terms of the count and percentage share of each strategy. The count and percentage share of strategies among the regions are also different. However, in the case of the four most numerous regions, which will be compared in the empirical study, the percentage share of particular strategies does not seem to differ so much, as presented in Table 5.6. The group of Eastern Asia seem to outstand the most, as the share of equity funds is the highest among all four regions, the share of mixed asset funds is the lowest, and even the share of absolute return funds is less than the share of hedge funds.

Strategy / Region	Equity	Mixed Asset	Absolute Return	Hedge Funds	Total
Northern America	68.51%	28.22%	2.33%	0.93%	100%
Eastern Asia	75.20%	23.45%	0.42%	0.94%	100%
Northern Europe	66.01%	30.10%	3.03%	0.86%	100%
Western Europe	67.91%	24.97%	6.88%	0.24%	100%

Tab. 5.6. A percentage share of each strategy in four most numerous regions of a primary investment focus. Source: Author's own study

Similarly to the other issue-related studies discussed in Section 5.1., it was necessary to classify each fund as a qualitative or a quantitative one, as the Thomson Reuters Eikon database did not provide any problem-relevant classification. To divide the investment funds into quantitative and qualitative groups, a modified method originally developed by Harvey et al. (2017) was applied. It was a little modified as in this study it also employed the word *quantitative*. This word was rejected by Harvey et al. (2017) because it did not meet one of the three formal criteria established by the authors. On the other hand, in Abis (2018) this word had the greatest informativeness in terms of distinguishing a group of quantitative funds.

All things considered, the method of fund classification applied in this study consisted in looking for the following words in the fund objective description: *quantitative, model, algorithm, statistical, computer, system, approx* or words which were related for instance, *quantitative/quantitatively/quant, algorithm/algorithmically*. If any of these words appeared, a fund was classified as a quantitative one.

Table 5.7. presents the results of the application of this method in the case of the aforementioned basic sample of 295 088 funds. Additionally, the funds have been grouped by the main strategy according to the Lipper Global Classification scheme. Moreover, in order to compare the results of different split methods, Table 5.7. also provides the results of application of the original (unmodified) methods proposed by Chincarini (2014) and Harvey et al. (2017).

Strategy \ Approach		Chincarini (2014)		Harvey et al. (2017)		Author's approach		
		Qual	**Quant**	**Qual**	**Quant**	**Qual**	**Quant**	**Total**
Count	Absolute Return	6789	249	6719	319	6614	424	7038
	Equity	192806	4266	190462	6610	188538	8534	197072
	Hedge Funds	2986	139	2934	191	2895	230	3125
	Mixed Asset	86805	1048	84794	3059	84301	3552	87853
	Total	289386	5702	284909	10179	282348	12740	295088
Percentage	Absolute Return	96.46%	3.54%	95.47%	4.53%	93.98%	6.02%	-
	Equity	97.84%	2.16%	96.65%	3.35%	95.67%	4.33%	-
	Hedge Funds	95.55%	4.45%	93.89%	6.11%	92.64%	7.36%	-
	Mixed Asset	98.81%	1.19%	96.52%	3.48%	95.96%	4.04%	-
	Total	98.07%	1.93%	96.55%	3.45%	95.68%	4.32%	-

Tab. 5.7. The division of the basic sample of 295 088 investment funds into quantitative and qualitative funds, as well as by four main strategies according to the LGC scheme. The comparison of results delivered by split methods proposed in this study, by Chincarini (2014), and by Harvey et al. (2017). Source: Author's own study

According to the results of the basic sample split presented in Table 5.7., the share of quantitative funds classified using methodology originally proposed by Chincarini (2014) and Harvey et al. (2017) accounts for 1.93% and 3.45% of a whole basic sample, respectively. These fractions seem to be significantly smaller compared to the percentage share of quant funds distinguished in the studies by Chincarini (2014) and Harvey et al. (2017). In the study by Chincarini (2014), a group of quant funds constituted 39% of the total sample according to classification 1 and 17% according to classification 2. In the study by Harvey et al. (2017), systematic funds (as they called them) were responsible for 31% of the entire sample. The researchers focused on hedge funds retrieved from the HFR database; however, still in the group of hedge funds from the basic sample of this study only about 4.45% and 6.11% are quantitative according to the classification methods of Chincarini (2014) and Harvey et al. (2017), respectively. It is worth noting that in the group of hedge funds, in the basic sample of this study, quant funds constitute the largest fraction of all strategies considered according to all classification methods compared.

A relatively small percentage share of quant funds in the basic sample of this study, compared to the percentage share of quant funds in the studies by Chincarini (2014) and Harvey et al. (2017), may result from some limitations of the fund objective description provided by the Thomson Reuters Eikon database, which may contain insufficient information about the portfolio management process. The Thomson Reuters Eikon database did not provide any other description of investment fund operations and portfolio management process.

5.3. Research methodology

Studies on the performance of investment funds supported with the studies on the features of their returns in the context of the weak-form informational efficiency are not often met phenomenon and do not constitute any standard. However, the idea to conduct such a study, as was done for the needs of this thesis, was not exceptional. This concept was already used for instance by Zamojska (2012). Supplementing a study on performance of investment funds with a study on the features of their returns in the context of the weak-form informational efficiency may deliver some additional interesting information, especially on the predictability of future performance on the basis of the historical one.

Due to the need to conduct a study on the performance and weak-form informational efficiency of quantitative funds, as well as in order to ensure a clear structure, the study was divided into 3 separate parts:

1. Weak-form informational efficiency study
2. Performance study with the use of relative measures of portfolio performance as well as raw and excess returns
3. Performance study with the use of econometric models

The methodology of the first part of the study conducted for the needs of this thesis, namely, the weak-form informational efficiency study, is described in Section 5.3.1. It was developed in order to reach one of the research objectives of this study that consists in the evaluation of the weak-form informational efficiency of quantitative funds in relation to the weak-form informational efficiency of qualitative funds. This part of the study verifies the research hypothesis referring to the features of the returns of quantitative funds in the context of the weak-form informational efficiency. Furthermore, with a view to a further study on the performance of quantitative funds, the first part of the study examines the features of the returns of investment funds in terms of the application of some performance measures that assume the normality of return distribution. Additionally, the first part of the study provides information on the periods of a low weak-form efficiency of equity markets for the needs of the study on the performance of quantitative funds in such periods.

The second and third parts of the study were developed in order to achieve the research objective of this study that consists in the evaluation of the performance of quantitative funds in relation to the performance of qualitative funds. The methodology behind the second part of the study, namely the performance study with the use of relative measures of portfolio performance, is described in Section 5.3.2. Section 5.3.3. describes the methodology of the third part of the study, i.e., the performance study with the use of econometric models. The second and third parts of the study verify research hypotheses referring to the performance of the quantitative funds.

5.3.1. The first part of the study - weak-form informational efficiency testing

Referring to the research hypothesis related to the weak-form informational efficiency of quantitative funds, the first part of the study:

- verifies hypothesis H2 (a supplementary research hypothesis) and aims to answer the question whether quantitative funds are more weak-form informationally efficient than qualitative funds.

Moreover, the first part of the study makes an attempt to answer the following supplementary research questions:

- are quantitative funds more weak-form efficient than their relevant equity market benchmark selected in this study?
- do differences in the weak-form efficiency between quantitative and qualitative funds differ between the groups of funds distinguished in terms of strategy and region of a primary investment focus?
- are larger quantitative funds in terms of managed total net assets more weak-form efficient than smaller quantitative funds?

It is worth mentioning that the first part of the study also delivers some necessary information for the needs of further parts of the study, i.e., the ones related to the performance of quantitative funds. Taking this into account, the first part of the study, especially:

- provides information on the weak-form efficiency of relevant equity markets benchmarks, which is essential in terms of the verification of hypothesis H3 (a supplementary research hypothesis), as well as in terms of answering the question whether quantitative funds perform better than qualitative funds in periods of low weak-form efficiency of equity markets,
- provides information on the normality of distribution of fund returns that is essential in terms of the application of some performance measures requiring the normality of returns.

Weak-form efficiency is verified with the use of four statistical tests, where two are the statistical tests for the martingale difference hypothesis (MDH), and the other two are the statistical tests for normality. The hypothesis H2 is verified with the use of a comparative analysis of results provided by the MDH and normality test for quantitative and qualitative funds.

Statistical tests for the martingale difference hypothesis (MDH) applied in this study, based on the linear measures of dependence, constitute notable recent contributions to the category of the MDH tests according to Charles, Darné, and Kim (2011):

- the automatic Portmanteau test for serial correlation proposed by Escanciano and Lobato (2009), constituting a modification of the Box-Pierce test. In this modification, the order of the autocorrelation is chosen automatically. There is no need to use bootstrap procedure to estimate the critical values, as its asymptotic null distribution is chi-square with one degree of freedom. Moreover, the authors emphasise the robustness of the test to the presence of the conditional heteroskedasticity of an unknown form. To run this test in R, a function Auto.Q from the package vrtest was used.
- the wild bootstrapped automatic variance ratio test under conditional heteroskedasticity proposed by Kim (2009), constituting a modification of the automatic variance ratio test proposed by Choi (1999). According to Kim (2009), the wild bootstrapped automatic variance ratio test shows no size distortion in small samples and has substantially higher power than its competitors, such as the wild bootstrapped Chow–Denning test and the Chen–Deo test. To run this test in R, a function AutoBoot.test from the package vrtest was used.

Two other statistical tests used in the first part of the study are the normality tests of Lilliefors and D'Agostino-Pearson. As opposed to the abovementioned MDH tests, tests for normality are considered strict random walk tests. Normality tests are conducted not only to verify the weak-form efficiency, but also to check if the application of some performance measures is justified. These performance measures will be discussed in the following section, raising the issue of a methodology of the second part of the study.

To run the abovementioned tests, a rolling window approach was applied. The applied approach consisted in performing tests for 60-month windows of monthly logarithmic returns of net asset values (hereinafter NAV) retrieved at the end of each month, rolled by 12 months (the next window began 12 months from the beginning of the previous window). A test was run only if, in a given window, a fund had at least 90% of a maximum number of observations. A required minimum number of observations to run a test was 54 (a maximum number of observations was 60). This approach was applied to all funds from the basic sample described in Section 5.2. in the research period from 01/01/2000 to 31/12/2020.

To make the applied rolling window approach easier to understand, the R algorithm checked if each fund from the basic sample described in Section 5.2. had a required number of observations (at least 54 logarithmic returns) in the first 60-month period from 01/01/2000 to 31/12/2004. If a fund met this requirement, each test was run for this fund in this window. If the condition was not met, the tests were not run. The algorithm repeated this procedure for the next window rolled by 12 months, i.e., for a window in the period from 01/01/2001 to 31/12/2005. The last window for which the process was repeated was a window in the period from 01/01/2016 to 31/12/2020. A rolling window method was applied to check whether the results varied over time and to find the periods of a low weak-form efficiency of equity markets, essential in terms of the verification of the H3 hypothesis. The length of window and its rolling were chosen arbitrarily.

Results will be presented separately for each test as a percentage of cases in which quantitative funds, qualitative funds and equity markets could be considered weak-form efficient at the significance level of 0.05. When discussing results, quantitative funds, qualitative funds and equity markets will be referred to as *categories*. Moreover, the results for quantitative funds and qualitative funds will be presented as a percentage of cases in which they could be considered weak-form efficient, weighted by their average total net assets (TNA). It was decided to apply total net assets (TNA) instead of assets under management (AUM) due to incomplete data related to AUM in the Thomson Reuters Eikon database. The application of AUM would significantly decrease the size of the sample.

The percentage share of efficient funds was calculated for all windows in the entire research period from 01/01/2000 to 31/12/2020 and for each time window separately. Furthermore, the results will also be presented for each of four main strategies according to the Lipper Global Classification scheme, as well as for each of the four most numerous geographic regions of a primary investment focus.

The same rolling window approach was applied to run tests for the logarithmic returns of stock market indices related to the countries of a primary investment focus of the examined investment funds. A primary selection criterion for a stock market index was its breadth, understood as a part of stock market it reflected. Thus, the most preferable ones were the all-share stock market indices. However, due to some limitations like the lack of such indices or a short period of data that often covered just a small part of the entire research period from 01/01/2000 to 31/12/2020, selected indices did not consist just of the all-share ones. Moreover, for the reasons mentioned above, a sample of the indices consisted of both price and total return indices. Stock market indices employed in this study are enumerated in Table 5.8. This table includes a country of a primary investment focus, its region according to The United Nations geo-scheme, a selected stock market index that is related to a given country of a primary investment focus, and a stock exchange related to the index selected. The results of the study on the weak-form informational efficiency of quantitative funds (the first part of the study) will be discussed in Chapter 6.

Region	**Country**	**Exchange**	**Index**
Northern America	United States	New York Stock Exchange, NASDAQ	S&P 500
	Canada	Toronto Stock Exchange	S&P/TSX Composite Index
Eastern Asia	China	Shanghai Stock Exchange	SSE Composite Index
	Japan	Tokyo Stock Exchange	Nikkei 225
	South Korea	Korea Stock Exchange	KOSPI
	Hong Kong	Hong Kong Stock Exchange	Hang Seng Index

Northern Europe	United Kingdom	London Stock Exchange	FTSE 250 Index
Western Europe	France	Euronext Paris	CAC All-Share Index
	Germany	Frankfurt Stock Exchange	Prime All Share
	Switzerland	SIX Swiss Exchange	Swiss All Share Index
	Netherlands	Euronext Amsterdam	AEX All-Share Index
South America	Brazil	BM&F Bovespa	Bovespa Index
	Chile	Santiago Exchange	S&P/CLX IGPA
Southern Asia	India	National Stock Exchange of India	NIFTY 500 Index
Australia and NZ	Australia	Australian Securities Exchange	All Ordinaries Index
South-eastern Asia	Thailand	Stock Exchange of Thailand	SET
	Indonesia	Indonesia Stock Exchange	IDX Composite
	Malaysia	No exchange indicated by index provider	FTSE Malaysia Index
	Vietnam	No exchange indicated by index provider	FTSE Vietnam All-Share Index
	Singapore	No exchange indicated by index provider	FTSE Singapore Index
Southern Europe	Italy	Borsa Italiana	FTSE Italia All-Share Index
	Spain	Madrid Stock Exchange	Madrid Stock Exchange General Index
Southern Africa	South Africa	Johannesburg Stock Exchange	FTSE/JSE All Share Index
Eastern Europe	Russia	Moscow Exchange	MOEX Russia Index
	Poland	Warsaw Stock Exchange	WIG
Western Asia	Israel	Tel Aviv Stock Exchange	TA-125 Index
	Turkey	Borsa İstanbul	BIST All Shares Index
Central America	Mexico	Mexican Stock Exchange	S&P/BMV IPC CompMx

Tab. 5.8. Stock market indices employed in this study that are related to the countries of a primary investment focus of the examined investment funds. Source: Author's own study

5.3.2. The second part of the study - performance study with the use of relative measures of portfolio performance as well as raw and excess returns

Referring to research hypotheses related to the performance of quantitative funds, the second part of the study:

- verifies hypothesis H1 (the main research hypothesis) and aims to answer the question whether the performance of quantitative funds is higher than the performance of qualitative funds,
- verifies hypothesis H3 (a supplementary research hypothesis) and aims to answer the question whether quantitative funds perform better than qualitative funds in periods of a low weak-form efficiency of equity markets.

Moreover, the second part of the study makes an attempt to answer the following supplementary research questions:

- do quantitative funds outperform their relevant equity market benchmark selected in this study?

- do differences in performance between quantitative and qualitative funds differ between the groups of funds distinguished in terms of strategy and region of a primary investment focus?
- do larger quantitative funds in terms of managed total net assets perform better than smaller quantitative funds?
- are quantitative funds less risky than qualitative funds in terms of risk related to the distribution of returns they generate?
- are quantitative funds similar to qualitative funds in terms of the homogeneity of the performance generated and the correlation of the raw returns?

The abovementioned hypotheses were verified with the use of a comparative analysis of results received for quantitative and qualitative funds. Additionally, in order to expand the study and answer one of supplementary research questions, the results obtained for some relevant equity market benchmarks were included in the comparative analysis. The equity market benchmarks mentioned above were collected in the same way as described in Section 5.3.1. that discussed the methodology of the first part of the study.

The compared results were provided mainly by the relative measures of portfolio performance that were discussed in Chapter 4. The emphasis was put especially on them. Additionally, the average raw and excess returns were employed as well. Especially, the average excess returns constitute the essential component of many relative measures of portfolio performance discussed in Chapter 4. For the needs of this thesis and to simplify the nomenclature, raw and excess returns will also be called *unadjusted returns*. It will be interesting to verify whether the results provided by them and the relative measures of portfolio performance allow for drawing similar conclusions in a comparative analysis.

Performance measures applied in the second part of the study have been divided into five groups namely, raw and excess returns, classic performance measures, performance measures based on value at risk (VaR), performance measures based on lower partial moments (LPM), and performance measures based on maximum drawdown (MD). This division refers to the split proposed, for example, by Aldridge (2010) and Bacon (2008). A detailed split of performance measures applied in this study is as follows:

1. Unadjusted returns
    - Raw returns
    - Excess returns
2. Classic performance measures
    - Sharpe ratio
    - Treynor ratio
3. Performance measures based on the value at risk (VaR)
    - excess return on VaR
    - excess return on CVaR
4. Performance measures based on lower partial moments (LPM)

- Omega ratio
- Sortino ratio
- Kappa3 ratio

5. Performance measures based on maximum drawdown (MD)
   - Calmar ratio
   - Sterling ratio

In order to calculate performance measures mentioned above, a rolling window approach was applied, the same as in the case of the first part of the study. Also, the entire procedure and parameters of the rolling window method remained the same. The applied approach consisted in calculating performance ratios for 60-month windows of monthly logarithmic returns of NAV retrieved at the end of each month, rolled by 12 months (the next window began 12 months from the beginning of the previous window). A performance measure was calculated only if in a given window, a fund had at least 90% of a maximum number of observations. A required minimum number of observations to calculate a performance measure was 54 (a maximum number of observations was 60). This approach was applied for all funds from the basic sample described in Section 5.2. in the research period from 01/01/2000 to 31/12/2020.

The results will be presented as the average values of performance measures obtained for quantitative funds, qualitative funds, and equity market benchmarks. The results will also be presented as the average values of performance measures obtained for quantitative funds and qualitative funds, weighted by the average total net assets. Performance measures were calculated for all windows in the entire research period from 01/01/2000 to 31/12/2020 and for each time window separately. Moreover, in order to answer some of the supplementary research questions, the results will also be presented for each of four main strategies according to Lipper Global Classification scheme and for each of four most numerous geographic regions of a primary investment focus. In the process of the average results calculation, 5% of the lowest and 5% of the highest results were dropped. The removal of outliers will make the interpretation of results easier and at the same time, it will not bias the general conclusions.

Furthermore, using information about the windows (periods) of the lowest weak-form informational efficiency of equity markets, provided by the first part of the study, the average values of performance measures, as well as the average values of performance measures weighted by TNA will be compared between quantitative and qualitative funds in the windows marked by the lowest weak-form efficiency of the equity markets. This part of the study will verify the research hypothesis H3.

The majority of the measures were calculated with the use of functions included in R package PerformanceAnalytics. In order to calculate some of the ratios, some additional datasets were necessary, like data pertaining to the returns of equity market benchmark and the risk-free rate. The time series of equity market benchmark returns were retrieved as described in Section 5.3.1. Regarding risk-free rates, they were estimated as the yield of 3-month treasury bonds of countries of a primary geographic investment focus. When a 3-month treasury bond of a given country was not available, its yield was estimated using a linear OLS regression on the basis of the yield curve created by yields of five treasure bonds of this country with longer terms. The results of the study on the performance of quantitative funds with the use of the relative measures of portfolio performance as well as raw and excess returns (the second part of the study) will be discussed in Chapter 7.

5.3.3. The third part of the study - performance study with the use of econometric models

Referring to research hypotheses related to the performance of quantitative funds, the same as the second part of the study, the third part of the study:

- verifies hypothesis H1 (the main research hypothesis) and aims to answer the question whether the performance of quantitative funds is higher than the performance of qualitative funds,
- verifies hypothesis H3 (a supplementary research hypothesis) and aims to answer the question whether quantitative funds perform better than qualitative funds in periods of a low weak-form efficiency of equity markets.

Moreover, the third part of the study makes an attempt to answer the following supplementary research questions:

- do differences in performance between quantitative and qualitative funds differ between the groups of funds distinguished in terms of strategy and region of a primary investment focus?
- are quantitative funds less exposed to systematic risk than qualitative funds?

The abovementioned research hypotheses are verified with the use of the comparative analysis of the estimations of two models, i.e., the Capital Asset Pricing Model (CAPM) and Treynor-Mazuy model (TM). They were discussed in Chapter 4. The models were estimated for four groups distinguished in terms of the region of a primary investment focus, for four groups distinguished in terms of the main strategy according to Lipper Global Classification scheme, and for the general sample of all funds gathered together. This general sample will also be referred to as *the overall sample.* To verify the abovementioned hypotheses and answer the supplementary questions, both models were modified in such a way that they included additional variables that aimed to indicate some possible differences in performance and risk between the fund types compared, i.e., between quantitative and qualitative funds.

A modified CAPM model applied in this study can be described by the following equation (its classic version was discussed in Section 4.1.1.):

$$R_{it} - Rf_t = \alpha + \beta_1(Rm_t - Rf_t) + \beta_2 Type_i + \beta_3 Type_i(Rm_t - Rf_t) + \varepsilon \qquad (5.1.)$$

where:

R_{it} – the logarithmic monthly returns of fund i in time t,

Rf_t – the yield of the adequate risk-free rate in time t,
Rm_t – the logarithmic monthly returns of the adequate stock market index in time t,
$Type_i$– dummy variable that takes the value of 0 for qualitative fund and the value of 1 for quantitative fund.

The first component added to a classic CAPM model, i.e., $\beta_2 Type_i$ informs about the impact of the quantitative fund type on alpha (α) namely, a classic performance measure, also known as Jensen's alpha. If β_2 is positive (negative) and statistically significant, it means that the quantitative fund type has a positive (negative) impact on alpha (α). A positive impact on alpha (α) is understood as an increase in alpha (α), i.e., an increase in performance.

The second of the component added to a classic CAPM model, i.e., $\beta_3 Type_i(Rm_t - Rf_t)$ informs about the impact of the quantitative fund type on Beta1 (β_1) namely, a classic systematic risk measure. If β_3 is positive (negative) and statistically significant, it means that the quantitative fund type has a positive (negative) impact on Beta1 (β_1). A positive impact on Beta1 (β_1) is understood as an increase in Beta1 (β_1) i.e., increase in systematic risk.

A modified TM model applied in this study can be described by the following equation (its classic version was discussed in Section 4.1.2.):

$$R_{it} - Rf_t = \alpha + \beta_1(Rm_t - Rf_t)^2 + \beta_2(Rm_t - Rf_t) + \beta_3 Type_i + \beta_4 Type_i(Rm_t - Rf_t)^2 + \beta_5 Type_i(Rm_t - Rf_t) + \varepsilon \qquad (5.2.)$$

The first component added to a classic TM model i.e., $\beta_3 Type_i$ informs about the impact of the quantitative fund type on alpha (α) namely, a performance measure. If β_3 is positive (negative) and statistically significant, it means that the quantitative fund type has a positive (negative) impact on alpha (α). The same as in the case of the modified CAPM model, a positive impact on alpha (α) is understood as an increase in the alpha (α) i.e., increase in performance.

The second component added to a classic TM model i.e., $\beta_4 Type_i(Rm_t - Rf_t)^2$ informs about the impact of the quantitative fund type on Beta1 (β_1), which can be perceived as a measure of the ability of a portfolio manager to implement a correct strategy of active portfolio management and to adjust the level of a systematic risk to expected market conditions (market-timing skills). If β_4 is positive (negative) and statistically significant, it means that the quantitative fund type has a positive (negative) impact on Beta1 (β_1). A positive impact on Beta1 (β_1) is understood as an increase in Beta1 (β_1) i.e., increase in market-timing skills.

The third of the added components i.e., $\beta_5 Type_i(Rm_t - Rf_t)$ informs about the impact of the quantitative fund type on Beta2 (β_2) namely, a systematic risk measure. If Beta5 (β_5) is positive (negative) and statistically significant, it means that quant funds have a positive (negative) impact on Beta2 (β_2). The same as in the case of the modified CAPM model, a positive impact on Beta2 (β_2) is understood as an increase in Beta2 (β_2) i.e., increase in systematic risk.

The modified CAPM and TM models were estimated using pooled OLS regressions. Standard errors in the pooled OLS regression were corrected using the Newey-West procedure with automatic lag selection. Fixed effects and random effects models were also considered;

however, the results of the Breusch and Pagan Lagrange multiplier test for random effects and the F test for no fixed effects indicated that random effects and fixed effects models would be applicable in the minority of windows. Thus, it was decided to apply pooled OLS regression only. The results of these tests are discussed in more detail in Chapter 8.

Models were also estimated in rolling windows. Nevertheless, in the case of the third part of the study it was decided to change the parameters of this method. The applied approach consisted in estimating models in 84-month windows rolled by 12 months (next window began 12 months from the beginning of the previous window). Only funds that had at least 80% of the maximum number of observations were included in the model in a given window. Thus, a minimum number of required observations in a window was 67 (a maximum number of observations was 84).

Furthermore, in order to verify the H3 hypothesis, the estimations of the modified CAPM and TM models will be carefully examined in the windows (periods) of the lowest weak-form efficiency of equity markets provided by the first part of the study. The time series of equity market benchmarks returns and risk-free rates were retrieved as described in Section 5.3.1. and Section 5.3.2., respectively. The results of the study on the performance of quantitative funds with the use of econometric models (the third part of the study) will be discussed in Chapter 8.

6. The results of the study on the weak-form informational efficiency of quantitative funds - the first part of the study

This chapter aims to discuss the results of the first part of the study, i.e., the one concerning the weak-form informational efficiency of quantitative funds. In addition to the discussion of the results of the first part of the study, this chapter presents the final research sample applied in the first and second part of the study. The main research objective of the weak-form informational efficiency study is to answer the question of whether quantitative funds are more weak-form informationally efficient than qualitative funds.

Section 6.1. presents the structure of the research sample of the first and second part of the study, as they are the same due to the application of the rolling window method with the same settings, i.e., 60-month windows moved by (rolled by) 12 months with a required minimum of 90% of monthly observations in each window. Due to the same final research samples applied in the first and second part of the study, the research sample applied in the second part of the study will not be discussed again in Chapter 7. Section 6.2. discusses the results of tests for the martingale difference hypothesis (MDH) and Section 6.3. discusses the results of normality tests. The results are concluded in Section 6.4.

The structure of the final research sample and the results of the study are presented:

- for all funds together without any division;
- within the division into selected four main strategies according to the Lipper Global Classification scheme, namely, equity funds, mixed asset funds, hedge funds, and absolute return funds;
- within the division into selected four most numerous regions of a primary investment focus, namely, Northern America, Eastern Asia, Northern Europe, and Western Europe.

Moreover, due to a comparative nature of this study, as well as in order to achieve the research objectives, the results are also presented for qualitative funds, quantitative funds, and stock market indices (markets) separately.

6.1. The structure of the research sample in the first and second part of the study

This section presents the structure of the research sample in the first and second part of the study. Some terms used in the tables and figure further clarification:

- unique funds – the number/percentage of unique quantitative funds, qualitative funds,
- windows tested – the number/percentage of the rolling windows tested (not a number of tests run).

Table 6.1. presents the number and the percentage share of unique quantitative funds and qualitative funds in the entire research period from 01/01/2000 to 31/12/2020, which were qualified to the first and second part of the study, as they met the requirement of at least 54 monthly returns in at least one 60-month rolling window (the requirement of at least 90%

observations in a window). Table 6.1. also presents the number and the percentage share of all rolling windows tested (not a number of tests run) for quantitative funds and qualitative funds. The number of unique funds and the number of windows tested presented in Table 6.1. show that quantitative funds constitute just a fraction of a whole research sample. Quantitative funds constituted around 4.5% in both all unique funds and all windows tested. The final research sample of the first and second part of the study consisted of 68 794 unique qualitative funds and 3 267 unique quantitative funds. 480 844 rolling windows were tested for qualitative funds and 22 710 for quantitative funds.

	Count		Percentage	
Fund type	Windows tested	Unique funds	Windows tested	Unique funds
Qualitative	480 844	68 794	95.49%	95.47%
Quantitative	22 710	3 267	4.51%	4.53%
Total	503 554	72 061	100.00%	100.00%

Tab. 6.1. The number of unique quantitative and qualitative funds, the number of their windows tested, as well as their percentage share in the entire research period from 01/01/2000 to 31/12/2020. Source: Author's own study

Table 6.2. presents the number and the percentage share of quantitative and qualitative funds in the number of unique funds and all windows tested, in the entire research period from 01/01/2000 to 31/12/2020, divided into selected four main strategies according to the Lipper Global Classification scheme. The table suggests that the percentage share of quantitative funds is strategy-dependent, as in most cases some slight differences can be observed. It ranges from about 4.3% to 8.2% taking into account unique funds and from about 4.1% to 7.0% taking into account windows tested. The only outstanding group in terms of the share of quantitative funds in the number of unique funds and windows tested is the hedge fund group. Their share in the unique funds number is 8.22%. In the case of the share in windows tested number, its 7.02%.

		Count		Percentage	
Strategy	Fund type	Windows tested	Unique funds	Windows tested	Unique funds
Absolute Return	Qualitative	8 686	1 730	95.82%	94.85%
	Quantitative	379	94	4.18%	5.15%
Equity	Qualitative	337 037	45 186	95.94%	95.72%
	Quantitative	14 256	2 018	4.06%	4.28%
Hedge	Qualitative	3 336	413	92.98%	91.78%
	Quantitative	252	37	7.02%	8.22%
Mixed Asset	Qualitative	131 785	21 465	94.40%	95.05%
	Quantitative	7 823	1 118	5.60%	4.95%

Tab. 6.2. The number of unique quantitative and qualitative funds, the number of their windows tested, as well as their percentage share in the entire research period from 01/01/2000 to 31/12/2020, divided into selected four main strategies according to the LGC scheme. Source: Author's own study

According to Figure 6.1., a group of equity funds is the most numerous one in terms of both unique funds and windows tested. This group is responsible for 69.76% of windows tested and 65.51% of unique funds. Mixed asset funds are the second largest group in the sample.

They account for 27.72% of windows tested and 31.34% of unique funds. The third largest group are absolute return funds that constitute 1.80% of windows tested and 2.53% of unique funds. Hedge funds are the smallest group of funds that account for 0.71% of windows tested and 0.62% of unique funds.

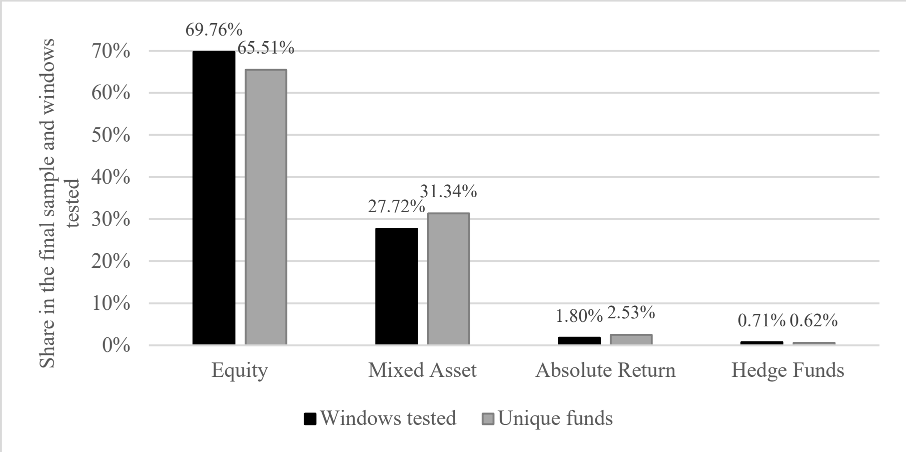

Fig. 6.1. The percentage share of selected four main strategies (according to the LGC scheme) in the final sample (unique funds) and windows tested (windows tested). Source: Author's own study

The final sample could also be broken down to 13 groups distinguished in terms of the region of a primary investment focus. Nevertheless, due to a very small count of unique funds and windows tested in some of these groups, it was arbitrarily decided to focus on just four most numerous groups. According to Table 6.3., the groups of funds with a primary geographic investment focus in Eastern Asia and Northern Europe had the lowest share of quantitative funds among the four compared regions. It amounted to about 3% in terms of both share in unique funds and share in windows tested. Investment funds primarily investing in Northern America had the highest share of quantitative funds among the four compared regions of about 5.5% in terms of both share in unique funds and share in windows tested. The share of quantitative funds in the number of unique funds in the case of funds primarily investing in Western Europe amounted to about 5.5%. Their share in windows tested amounted to about 4%.

		Count		Percentage	
Region	Fund type	Windows tested	Unique funds	Windows tested	Unique funds
Eastern Asia	Qualitative	71 303	11 338	97.20%	97.30%
	Quantitative	2 052	315	2.80%	2.70%
Northern America	Qualitative	277 143	38 629	94.43%	94.40%
	Quantitative	16 358	2 292	5.57%	5.60%
Northern Europe	Qualitative	34 193	4 741	97.32%	97.31%
	Quantitative	942	131	2.68%	2.69%
Western Europe	Qualitative	39 297	5 035	95.76%	94.71%
	Quantitative	1 738	281	4.24%	5.29%

Tab. 6.3. The number of unique quantitative and qualitative funds, the number of their windows tested, as well as their percentage share in the entire research period from 01/01/2000 to 31/12/2020, divided into four most numerous regions of a primary investment focus. Source: Author's own study

According to Figure 6.2., a group of funds with a primary investment focus in Northern America is the most numerous one in terms of both unique count and windows tested. This group accounts for 58.29% of windows tested and 56.79% of unique funds (when calculating percentage shares in this section all 13 regions were taken into account). Funds with a primary investment focus in Eastern Asia are the second largest group in the sample. They accounted for 14.57% of windows tested and 16.17% of unique funds. The third largest group are funds with an investment focus in Western Europe. They constitute 8.15% of windows tested and 7.38% of unique funds. Funds with a geographic investment focus in Northern Europe are the fourth largest group in the research sample. They are responsible for 6.98% of windows tested and 6.76% of unique funds. The four groups mentioned above accounted for about 88% of all windows tested and about 87% of all unique funds (considering all 13 regions).

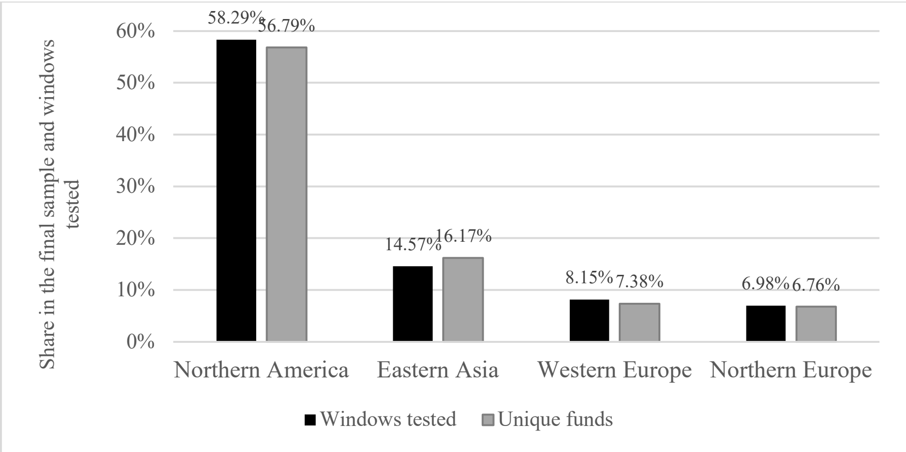

Fig. 6.2. The percentage share of four most numerous regions of a primary investment focus in the final sample (unique funds) and windows tested (windows tested). Source: Author's own study

6.2. Tests for the martingale difference hypothesis (MDH)

This section discusses the results of the study on the weak-form informational efficiency of quantitative funds conducted with the use of two martingale difference hypothesis (MDH) tests, namely, the automatic Portmanteau test for serial correlation and the wild bootstrapped automatic variance ratio test under conditional heteroskedasticity, which are less strict and more suited to actual financial time series. Due to a comparative character of this study, these tests will also be conducted for the relevant stock market indices and qualitative funds. Due to the long names of the two abovementioned tests, the automatic Portmanteau test for serial correlation will be referred to as *the automatic Portmanteau test* in text and *Automatic Portmanteau* in plots. The wild bootstrapped automatic variance ratio test under conditional heteroskedasticity will be referred to as *the automatic variance ratio test* in text and *Wild-bootstrap auto VR* in plots.

The results of the abovementioned tests will be presented as a percentage of cases in which the MDH tests indicated that monthly logarithmic returns in a rolling window were weak-form informationally efficient. In the case of quantitative and qualitative funds, the percentage of cases in which funds were weak-form informationally efficient was additionally weighted by their average total net assets (TNA). This procedure will allow to observe differences in efficiency between larger and smaller funds in terms of their total net assets (TNA).

The percentage of cases/windows in which stock market indices were weak-form efficient is marked as *Market*. The percentage of cases in which quantitative and qualitative funds were weak-form efficient is marked as *Quant* and *Qual*, respectively. The percentage of cases in which quantitative and qualitative funds were weak-form efficient that is weighted by their average total net assets is marked as *Quant WAVG* and *Qual WAVG*, respectively. The abbreviation *WAVG* refers to a weighted average. This study considers the percentage of cases in which market, quantitative funds, and qualitative funds were efficient as a proxy for their weak-form efficiency. Thus, in the interpretation of results, a higher percentage of efficient cases will be interpreted as a higher efficiency of one of the categories.

The results will be presented for each MDH test separately, for the entire research period from 01/01/2000 to 31/12/2020 (all windows tested in the entire research period were taken into account in the calculation of the percentage of efficient time series), as well as for each window individually (only time series from a specific window were taken into account in the calculation of the percentage of efficient time series). Moreover, the results will be grouped by strategy, i.e., they will be presented for selected four main strategies according to Lipper Global Classification scheme. The results will also be grouped by the region of a primary investment focus. The results will be presented for four most numerous regions of a primary investment focus. Additionally, the results for each window were used to make a pairwise comparison between the types/categories (Market, Quant, Qual, Quant WAVG, and Qual WAVG). The aforementioned pairwise comparison shows the percentage of windows (cases) in which one type/category had a higher percentage of efficient time series than another one.

Overall results

Figure 6.3. presents the percentage of windows, as well as the percentage of windows weighted by the average total net assets (TNA), in the entire research period from 01/01/2000 to 31/12/2020, for which the MDH tests indicated the weak-form informational efficiency. The results pertain to the entire research sample qualified to the first part of the study.

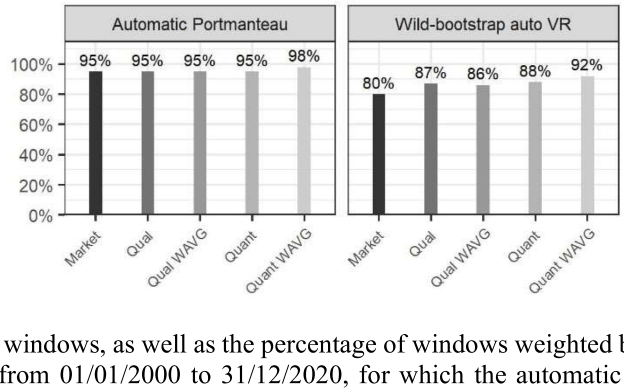

Fig. 6.3. The percentage of windows, as well as the percentage of windows weighted by total net assets (TNA), in the entire research period from 01/01/2000 to 31/12/2020, for which the automatic Portmanteau test for serial correlation (Automatic Portmanteau) and the wild bootstrapped automatic variance ratio test under conditional heteroskedasticity (Wild-bootstrap auto VR) indicated the weak-form informational efficiency. Source: Author's own study

The results provided by the automatic Portmanteau test do not differ much between the categories. In the case of this test, around 95% of the rolling windows of the markets, qualitative funds, qualitative funds weighted by TNA and quantitative funds turned out to be efficient. Only the percentage of the quantitative funds' windows tested weighted by TNA outstands, but not that much, and reaches about 98% of efficient windows. These results may suggest that the markets, qualitative funds, and quantitative funds had a similar and very high efficiency rate; however, larger quantitative funds in terms of TNA they manage were even more often weak-form efficient. In other words, the returns of a great majority of markets and funds, especially the quant ones managing larger TNA, turned out to be the time series of martingale increments. In the context of the weak-form informational efficiency, these results suggest that in most cases there was no possibility to predict a future performance on the basis of the historical one and to generate abnormal returns. A higher efficiency rate of the quant funds managing larger TNA may result from a quantitative portfolio management process they utilize. More advanced quantitative portfolio management process, which can be applied by more developed quant funds with larger amounts of assets managed, may positively affect the informational efficiency, for instance, by limiting some behavioural errors. It can be dome by applying some more reliable investment strategies or diversifying portfolio in a better way.

The results provided by the automatic variance ratio test are slightly different. There were notably fewer cases of the efficiency of the market compared to the other fund categories. Also, the general frequency of efficient cases across all categories was lower than in the case of the first MDH test discussed. The results of quantitative and qualitative funds did not differ much but, again, the weighted percentage of quantitative funds turned out to be slightly higher. To sum up, according to the second MDH test, the markets were less frequently efficient compared to quant and qual funds. However, this percentage was still high, reaching 80%. The quant funds seemed to be efficient as frequently as the qual funds; however, the quant funds managing larger TNA tended to be efficient even more often. This situation was also observable in the case of results provided by the automatic Portmanteau test. It may suggest that especially in the case of quantitative funds managing larger TNA, the possibility of predicting future performance on the basis of the past is very low. The same refers to generating abnormal returns.

The analysis of the results over the windows may provide some valuable information on the behaviour of efficiency over time. Figure 6.4. presents the percentage of windows, as well as the percentage of windows weighted by TNA, which turned out to be weak-form informationally efficient according to the MDH tests in each time window. In order to calculate the results presented in Figure 6.4., a rolling window method with 60-month windows and 12-month rolling was applied. This method was discussed in detail in Chapter 5.

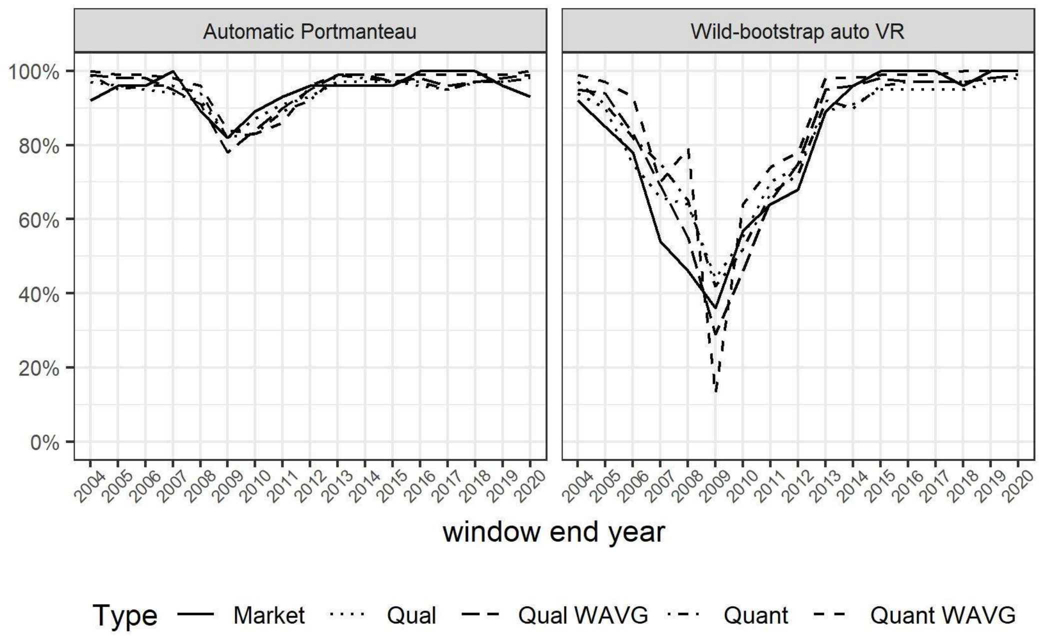

Fig. 6.4. The percentage of windows, as well as the percentage of windows weighted by total net assets (TNA), in each time window, for which the automatic Portmanteau test for serial correlation (Automatic Portmanteau) and the wild bootstrapped automatic variance ratio test under conditional heteroskedasticity (Wild-bootstrap auto VR) indicated the weak-form informational efficiency. Source: Author's own study

The first thing which stands out is a common decrease in efficiency up to the window ending in 2009 and a common and systematic recovery of efficiency in the following windows across all categories examined. The aforementioned decrease can be observed in the case of both MDH tests. Nevertheless, in the case of the automatic variance ratio test, the decrease is more severe. In more stable periods, the levels of efficiency across the categories in both MDH tests were mostly similar ranging between 90% and 100%. However, the results of the automatic variance ratio test plunged much more in periods of instability, suggesting that this test is more fragile to market shocks.

A decrease in efficiency across the examined categories up to the window ending in 2009 is most likely related to the global financial crisis 2007-2008 (hereinafter referred to as the global financial crisis). The results of the foregoing studies on the impact of the global financial crisis on the weak-form informational efficiency of equity markets suggest mixed conclusions. For instance, according to studies by Horta et al. (2014), Sensoy and Tabak (2015), Anagnostidis et al. (2016), and Mensi et al. (2017), the global financial crisis negatively affected the weak-form informational efficiency of equity markets. On the other hand, Katris and Daskalaki (2013), as well as Singh, Deepak, and Kumar (2015) proposed that the global financial crisis had no significant impact on the weak-form informational efficiency of equity markets.

It is worth nothing that the percentage of efficient windows across all categories behaved similarly in the periods related to the global financial crisis. It may suggest that all fund categories examined are not immune to equity market shocks and are similarly affected by them.

After the windows of recovery, the results of the automatic Portmanteau test suggest that the percentage of efficient markets started to fall from the window ending in 2018. However, this time not that much as in the case of the global-financial-crisis-related periods. Moreover, in this case, the efficiency of fund categories did not plunge along with the efficiency of the market.

Paying more attention to an outstanding window ending in 2009, Figure 6.5. shows the percentage of windows, which turned out to be weak-form informationally efficient only in the window ending in 2009. The results of the tests applied suggest ambiguous conclusions. According to results provided by the automatic Portmanteau test, in the window ending in 2009, the percentages of efficient funds and efficient markets were very similar. However, according to results provided by the automatic variance ratio test, in the window ending in 2009, the percentages of efficient funds and efficient markets were clearly different. The percentage of efficient quantitative and qualitative funds was similar (categories not weighted by TNA) and higher than the percentage of efficient markets. On the other hand, the percentage of efficient quantitative and qualitative funds weighted by TNA was lower than the percentage of efficient markets. In the case of quant funds, this difference was even larger. Thus, the results provided by the automatic variance ratio test may suggest that funds with larger TNA (especially the quant ones) were less efficient in the crisis-related period. This is surprising, as taking into account Figure 6.3. (presenting results for all windows in the entire research sample), in the quant fund group, the percentage of efficient windows weighted by TNA was the highest. Larger funds (especially the quant ones) in terms of managed TNA may be less immune to equity market shocks due to higher dependence on equity markets. A similar behaviour of the efficiency of the categories compared is likely to be explained by the majority share of equity funds in the overall sample. Equity funds are especially exposed to the conditions on equity markets. What is even more important, the results of the automatic variance ratio test suggest that quantitative portfolio management processes applied by quant funds managing larger TNA failed in periods of instability in terms of the weak-form efficiency.

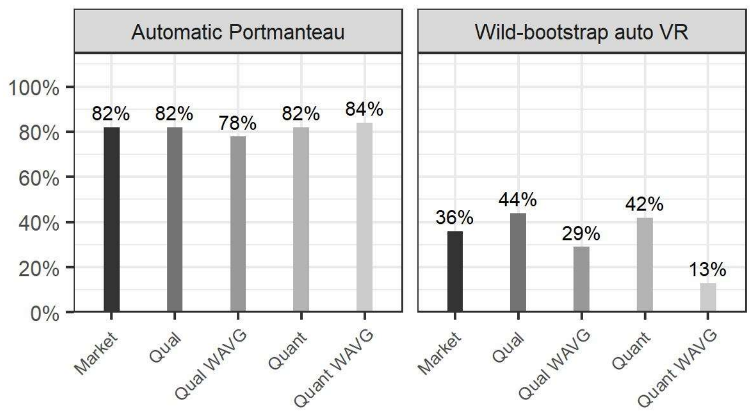

Fig. 6.5. The percentage of windows, as well as the percentage of windows weighted by total net assets (TNA), in the window ending in 2009, for which the automatic Portmanteau test for serial correlation (Automatic Portmanteau) and the wild bootstrapped automatic variance ratio test under conditional heteroskedasticity (Wild-bootstrap auto VR) indicated the weak-form informational efficiency. Source: Author's own study

Data presented in Figure 6.4. were used to make a pairwise comparison of the efficiency results of the market and distinguished groups of funds in each time window. The results of this comparison are presented in Table 6.4. as a percentage of cases (time windows) in which a group of winners (rows) was more weak-form informationally efficient than a group of losers (columns). Table 6.4. includes the results of a pairwise comparison of the results of both MDH tests. This type of comparison is also used in the following sections of this chapter. The sum of win rates of two compared categories does not have to be equal to one, as there could have been a draw in some windows. While analysing the results presented in Table 6.4., it is important to remember that it is not a symmetric matrix.

In order to make the interpretation of Table 6.4. clear, the following example may be helpful. A value of 0.41 at the top of the first column with numeric data refers to a percentage of cases (41%) in which qualitative funds turned out to be more often efficient compared to equity markets. The results presented in Table 6.4. suggest that quantitative funds were more frequently more efficient than markets compared to qualitative funds; however, the difference is not substantial. Funds with larger TNA were more successful in this respect, especially the quant ones. What is also worth mentioning is that quant funds were more frequently more efficient than qualitative funds. However, this difference is not substantial. Nevertheless, the situation looks different in the case of the quant funds managing larger TNA. These funds were clearly more frequently more efficient than both categories of qualitative funds.

MDH tests - Overall results					
	Losers				
Group	Market	Qual	Qual_WAVG	Quant	Quant_WAVG
Market		0.5	0.44	0.44	0.29
Qual	0.41		0.24	0.26	0.09
Qual_WAVG	0.53	0.71		0.47	0.09
Quant	0.5	0.56	0.26		0.09
Quant_WAVG	0.62	0.91	0.85	0.85	

Tab. 6.4. The results of a pairwise comparison that indicate the percentage of cases (time windows) in which one group (rows) was more weak-form informationally efficient than another one (columns) according to both MDH tests. Source: Author's own study

Table 6.4. takes into account the results of both MDH tests. According to the results of the automatic variance ratio test presented in Figure 6.5. the efficiency of larger quant funds in terms of managed TNA suffered especially severely in the period related to the global financial crisis. These results are not in line with the results provided by the automatic Portmanteau test. Nevertheless, taking into account that the larger quant funds suffered the most according to the automatic variance ratio test in the period related to the global financial crisis and were marked by the highest winning rates in a pairwise comparison presented in Table 6.4., larger quant funds in terms of TNA managed may do great in periods of the market stability when it comes to weak-form informational efficiency; however, they may be very fragile to market shocks. As was already mentioned, equity funds constitute the majority of the research sample and thus they may affect the results the most. Larger equity funds in terms of managed TNA may focus

on popular and liquid assets, which may be affected the most by the irrational decisions of the market participants in the instable periods. It is worth examining whether similar results will be observed in the case of particular strategies and regions of a primary investment focus. Worse results of larger quant funds may also be related to the meltdown of the quant funds during the global financial crisis that was studied, for instance, by Khandani and Lo (2011) who proposed that this issue was caused by some errors in the investment strategies of these funds. However, due to the inconsistency of the results of the two applied MDH tests, they should be treated with caution.

Results by strategy

This section presents the results of the MDH tests grouped by four main strategies according to the Lipper Global Classification scheme. It refers to a supplementary research question on whether differences in the weak-form informational efficiency between quantitative and qualitative funds differ between the groups of funds distinguished in terms of strategy. Figure 6.6. presents the results of the MDH tests as a percentage of windows (windows tested percentage), as well as a percentage of windows weighted by the average total net assets (TNA) that turned out to be efficient in the entire research period from 01/01/2000 to 31/12/2020.

Results presented in Figure 6.6. constitute a basis for drawing mixed conclusions. In the case of the automatic Portmanteau test for all strategies except for the hedge funds, the results are similar for all five analysed categories. For the same three strategies, but this time in the case of the automatic variance ratio test, the results of funds are clearly higher compared to the results of the market. The situation looks different in the case of hedge funds that generally generated worse results compared to the market. In this group, quant funds had clearly better results than qual funds. Taking into account both tests, in the case of absolute return and equity funds, especially quant funds with higher TNA had better results compared to the other categories.

All conclusions drawn on the basis of the overall results (Figure 6.3.) seem to hold only in the case of equity funds. It is in line with the presumption according to which the equity funds constituting the greatest share in the overall sample had the biggest impact on its results. However, the results of absolute return and mixed asset funds do not seem to deviate much from those of equity funds. Especially the results of absolute return funds seem to allow for drawing conclusions similar to the ones of equity funds and overall sample. It may be surprising, as the principles of the operations of absolute return funds are much different compared to those of equity funds. As opposed to equity funds, absolute return funds aim to generate positive returns with low volatility, which are independent of the conditions on financial markets and conventional benchmarks.

The results of hedge funds deviate the most from the overall results. Hedge funds are not limited by legal regulations as much as the other funds. Thus, they can employ innovative and risky investment strategies mostly with caring less about volatility of returns, which can explain their weakest results among the other strategies. At the same time, it is the only group in which the difference between quant and qual funds is clear, especially in the case of the automatic variance ratio test. Especially in the group of hedge funds, in which managers have a relatively big freedom when it comes to making investment decisions, the quantitative portfolio management process may positively affect the informational efficiency, for instance, by limiting some behavioural errors of managers, applying some more reliable investment strategies, or diversifying portfolio in a better way.

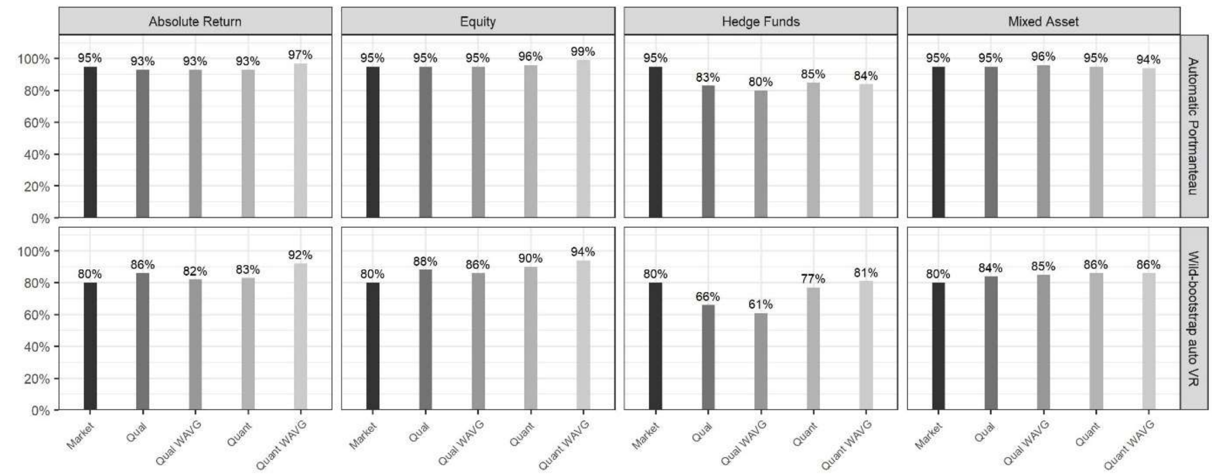

Fig. 6.6. The percentage of windows (windows tested percentage), as well as the percentage of windows weighted by total net assets (TNA) in the entire research period from 01/01/2000 to 31/12/2020, for which the automatic Portmanteau test for serial correlation (Automatic Portmanteau) and the wild bootstrapped automatic variance ratio test under conditional heteroskedasticity (Wild-bootstrap auto VR) indicated weak-form informational efficiency, divided into selected four main strategies according to the LGC scheme. Source: Author's own study

According to Figure 6.7., only in the case of equity and mixed asset funds, a common plunge of efficiency across all categories up to the window ending in 2009 and then recovery was clearly visible the same as in the case of the overall sample. The similarity of the efficiency trends in the groups of equity and mixed asset funds to the efficiency trend of the overall sample may result from the fact that these two strategies contribute to the largest share in the overall sample. Moreover, the similarity of the efficiency trends in the groups of equity and mixed asset funds may result from the similarity of their strategies. One of the major similarities of these groups is that they both hold equities. Of course, in the case of mixed asset funds the proportion of equities is most likely to be lower. In the case of the remaining two groups, the trends were not as similar across the categories. In addition, they were not similar to trends featuring the overall sample. However, in the case of the majority of categories, the lowest levels of efficiency were observable by the windows ending in years related to the global financial crisis (windows ending in 2007-2009). In the following windows the efficiency mostly tended to recover across the strategies and categories. It suggests that, same as in the case of the overall sample, the global financial crisis could negatively affect the weak-form informational efficiency of funds from all four analysed strategies.

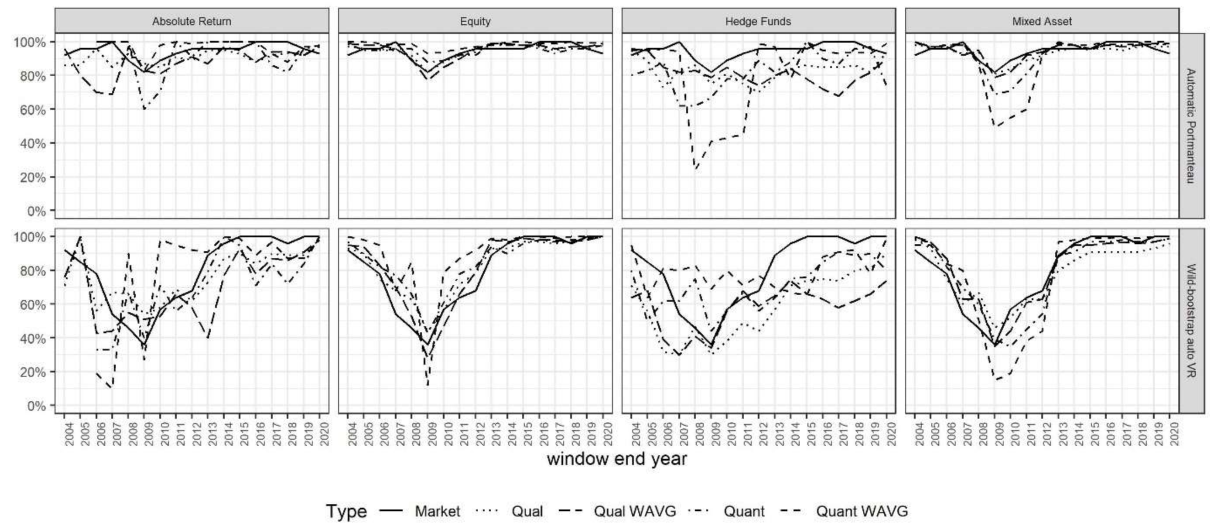

Fig. 6.7. The percentage of windows (windows tested percentage), as well as the percentage of windows weighted by total net assets (TNA) in each time window, for which the automatic Portmanteau test for serial correlation (Automatic Portmanteau) and the wild bootstrapped automatic variance ratio test under conditional heteroskedasticity (Wild-bootstrap auto VR) indicated weak-form informational efficiency, divided into selected four main strategies according to the LGC scheme. Source: Author's own study

Table 6.5. makes an attempt to summarise data presented in Figure 6.7. by presenting the results of a pairwise comparison that indicate the percentage of cases (time windows) in which one group (rows) was more weak-form informationally efficient than another one (columns) according to both MDH tests. A pairwise comparison was made for each strategy separately. Table 6.5. needs to be interpreted in the same way as explained in the example for Table 6.4.

When comparing the win rates of the not-weighted fund categories (Qual and Quant), in the case of all four examined strategies, quantitative funds more often had higher efficiency than qualitative funds. Comparing the win rates of weighted fund categories (Qual WAVG and Quant WAVG), the same was true. These results are in line with the overall results. Nevertheless, rarely any fund category managed to have a higher win rate than the market. Only the TNA-weighted quant fund category in the groups of the absolute return, equity, and mixed asset funds managed to do better than the market in this matter. The results of equity funds are those, which are the closest to the overall results. In the case of all four distinguished strategies, larger quant funds in terms of TNA they manage were more often efficient than the smaller quant funds.

MDH tests - Absolute Return					
	Losers				
Group	Market	Qual	Qual_WAVG	Quant	Quant_WAVG
Market		0.71	0.74	0.5	0.33
Qual	0.26		0.56	0.4	0.23
Qual_WAVG	0.26	0.29		0.4	0.2
Quant	0.37	0.6	0.57		0.13
Quant_WAVG	0.57	0.73	0.73	0.53	

MDH tests - Equity					
	Losers				
Group	Market	Qual	Qual_WAVG	Quant	Quant_WAVG
Market		0.44	0.38	0.38	0.15
Qual	0.47		0.26	0.26	0.03
Qual_WAVG	0.56	0.59		0.44	0.09
Quant	0.53	0.5	0.38		0.09
Quant_WAVG	0.71	0.88	0.88	0.88	

MDH tests - Hedge Funds					
	Losers				
Group	Market	Qual	Qual_WAVG	Quant	Quant_WAVG
Market		0.91	0.94	0.82	0.59
Qual	0.09		0.44	0.26	0.24
Qual_WAVG	0.06	0.47		0.35	0.26
Quant	0.18	0.74	0.62		0.29
Quant_WAVG	0.38	0.74	0.71	0.65	

MDH tests - Mixed Asset					
	Losers				
Group	Market	Qual	Qual_WAVG	Quant	Quant_WAVG
Market		0.62	0.56	0.53	0.35
Qual	0.29		0.21	0.32	0.32
Qual_WAVG	0.38	0.71		0.41	0.41
Quant	0.41	0.65	0.38		0.38
Quant_WAVG	0.44	0.65	0.53	0.53	

Tab. 6.5. The results of a pairwise comparison that indicate the percentage of cases (time windows) in which one group (rows) was more weak-form informationally efficient than another one (columns) according to both MDH tests, divided into selected four main strategies according to the LGC scheme. Source: Author's own study

Results by region

The results of the MDH tests for the four groups of the most numerous geographic regions of a primary investment focus are presented in Figure 6.8. The split of results was done in order to answer a supplementary research question whether differences in the weak-form informational efficiency between quantitative and qualitative funds differ between the groups of funds distinguished in terms of the region of a primary investment focus. The results of the most numerous group, i.e., the group of funds primarily investing in Northern America, resemble the overall results the most. Of course, the similarity of these groups may result from a major share of the group of funds primarily investing in Northern America in the overall sample. In this group, the efficiency among fund categories does not differ much; however, the TNA-weighted quant fund category has slightly higher results compared to the other fund categories. A similar pattern could also be observed in the overall results (Figure 6.3.) and mostly across all examined strategies (Figure 6.6.). The major difference between the results for the group of funds primarily investing in Northern America and the overall results is 100% of the efficient cases of the market. Nevertheless, the results for the market may be unreliable due to a small number of observations, so they should be treated with caution.

The results of the other three regions are a little different. In the case of Western Europe, funds are mostly more efficient than the market. Funds managing larger TNA seem to have lower efficiency, especially the quant ones. In the case of the remaining two groups of funds, namely, Easter Asia and Northern Europe, the results are similar across the fund categories.

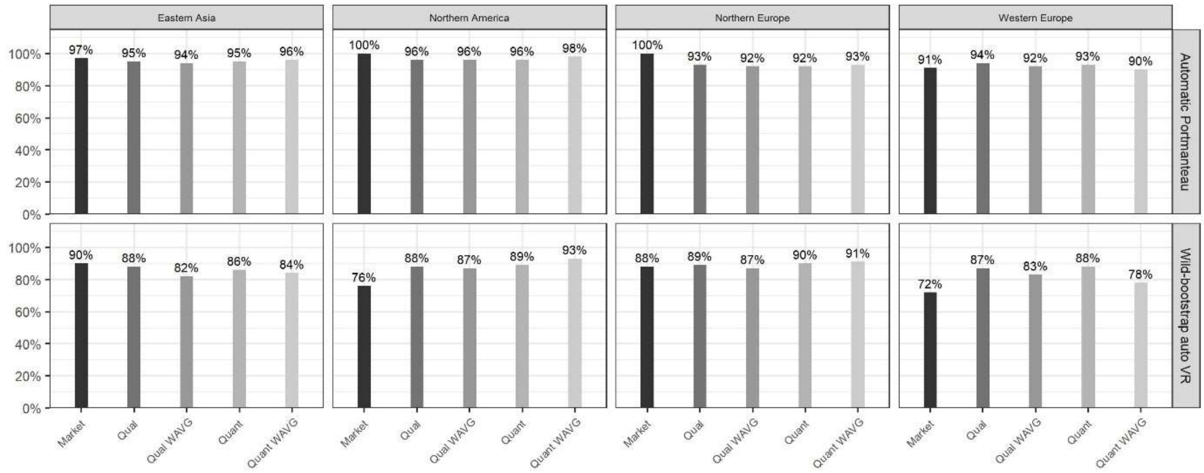

Fig. 6.8. The percentage of windows (windows tested percentage), as well as the percentage of windows weighted by total net assets (TNA) in the entire research period from 01/01/2000 to 31/12/2020, for which the automatic Portmanteau test for serial correlation (Automatic Portmanteau) and the wild bootstrapped automatic variance ratio test under conditional heteroskedasticity (Wild-bootstrap auto VR) indicated weak-form informational efficiency, divided into four most numerous regions of a primary investment focus. Source: Author's own study

At the beginning of the analysis of the results presented in Figure 6.9., it should be mentioned that the category of the market was not presented in Figure 6.9., as due to its small count in each window, its results might have been misguiding. Referring to Figure 6.9., a common plunge of efficiency up to the window ending in 2009 and then its recovery, which could be observed in the case of the overall sample, can be clearly observed only in the case of Northern America only. In other groups, plunges most likely related to the global financial crisis are visible in adjacent windows. Sometimes it is also category-dependent.

In some cases, significant plunges are also visible in other windows that do not seem to be related to the global financial crisis. For instance, a group of funds primarily investing in Eastern Asia had an additional observable plunge, i.e., the one in the window ending in 2005. The same pertains to Northern Europe. However, in this case, the plunge was visible in the window ending in 2017. Also, Western Europe had its common additional plunge that took place in the window ending in 2012. However, the decrease in efficiency across categories in periods related to the global financial crisis still remains a common feature of the regions examined. It suggests that the global financial crisis could have a negative impact on the efficiency of stock markets and funds across the most numerous regions, manifesting in a decrease of their efficiency. Some regions seem to be more negatively affected than the others. For instance, Northern Europe and Western Europe seem to be more robust to market shocks in terms of the market efficiency compared to Eastern Asia and Northern America.

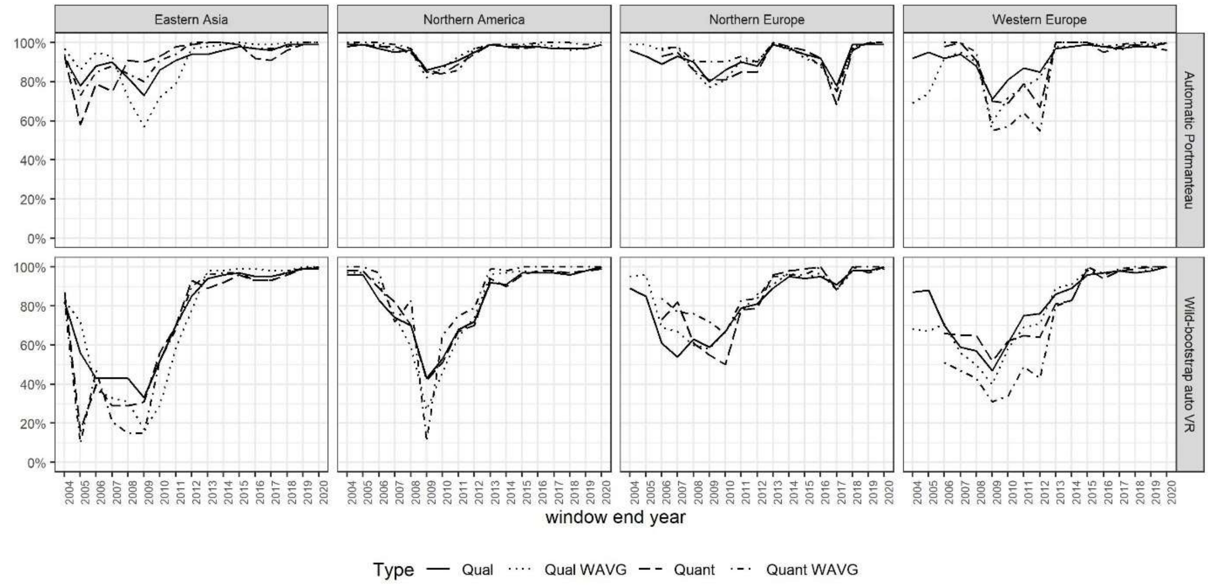

Fig. 6.9. The percentage of windows (windows tested percentage), as well as the percentage of windows weighted by total net assets (TNA) in each time window, for which the automatic Portmanteau test for serial correlation (Automatic Portmanteau) and the wild bootstrapped automatic variance ratio test under conditional heteroskedasticity (Wild-bootstrap auto VR) indicated weak-form informational efficiency, divided into four most numerous regions of a primary investment focus. Source: Author's own study

Similarly as in the case of grouping by strategy, Table 6.6. makes an attempt to summarise data presented in Figure 6.9. by presenting the results of a pairwise comparison that indicate the percentage of cases (time windows) in which one group (rows) was more weak-form informationally efficient than another one (columns) according to both MDH tests. The pairwise comparison was made for each of the four most numerous groups distinguished in terms of the geographic region of a primary investment focus. It should be noted that Table 6.6. does not include a pairwise comparison with a category of the market due to its small number of observations, the same as in the case of Figure 6.9.

The results presented in Table 6.6. differ much between the regions. When comparing the not-weighted categories of funds (Quant/Qual), in the groups of funds primarily investing in Eastern Asia and Northern America, qualitative funds were more frequently more efficient than quant funds. In the case of two remaining regions, the opposite was true. When comparing the weighted categories of funds (Quant WAVG/Qual WAVG), in the groups of funds primarily investing in Northern America and Northern Europe, quant funds were more frequently more efficient than qualitative funds. In all examined groups, except for the group of funds primarily investing in Western Europe, quant funds managing larger TNA were more frequently more efficient compared to smaller quant funds.

To sum up, the results of the pairwise comparison suggest that the compared groups of funds distinguished in terms of the region of a primary investment focus differ from each other. None of the regions provided the results that would be close to the overall ones.

MDH tests - Eastern Asia				
	Losers			
Group	Qual	Qual_WAVG	Quant	Quant_WAVG
Qual		0.32	0.5	0.32
Qual_WAVG	0.68		0.59	0.56
Quant	0.38	0.38		0.35
Quant_WAVG	0.53	0.32	0.44	

MDH tests - Northern America				
	Losers			
Group	Qual	Qual_WAVG	Quant	Quant_WAVG
Qual		0.24	0.38	0.12
Qual_WAVG	0.5		0.44	0.12
Quant	0.32	0.35		0.09
Quant_WAVG	0.79	0.74	0.85	

MDH tests - Northern Europe				
	Losers			
Group	Qual	Qual_WAVG	Quant	Quant_WAVG
Qual		0.35	0.43	0.2
Qual_WAVG	0.47		0.33	0.2
Quant	0.47	0.47		0.23
Quant_WAVG	0.73	0.63	0.57	

MDH tests - Western Europe				
	Losers			
Group	Qual	Qual_WAVG	Quant	Quant_WAVG
Qual		0.44	0.4	0.5
Qual_WAVG	0.32		0.37	0.53
Quant	0.5	0.53		0.4
Quant_WAVG	0.43	0.43	0.37	

Tab. 6.6. The results of a pairwise comparison that indicate the percentage of cases (time windows) in which one group (rows) was more weak-form informationally efficient than another one (columns) according to both MDH tests, divided into four most numerous regions of a primary investment focus. Source: Author's own study

6.3. Normality tests

The presentation of the results of normality test is systematized in the same way as the presentation of the results of the MDH tests. The same as in the case of the results of the MDH tests, the results presented in this section in the form of bar plots and line plots refer to the percentage of cases in which markets, quantitative funds, and qualitative funds, turned out to be weak-form informationally efficient. Due to strict assumptions of the normality tests, it is expected to observe fewer cases of the weak-form efficient time series for all examined categories.

Overall results

In line with the assumptions, as presented in Figure 6.10., the percentages of efficient windows across different categories are lower compared to the results of the MDH tests. Surprisingly, as opposed to the results of the MDH tests, all fund categories were less efficient than the markets, and, moreover, in the case of both tests, quant funds and especially the ones with larger TNA were less often efficient than any other category. What is also worth mentioning, for an overall sample, both normality tests allow for drawing similar conclusions. The indications of the results provided by both MDH tests were not so unambiguous. The dominance of the market in terms of the highest results of efficiency may come from the diversification of the stock market indices that can be treated as stock portfolios. According to the central limit theorem, the distribution of the returns of a well-diversified portfolio should be similar to a normal distribution (Zamojska, 2012).

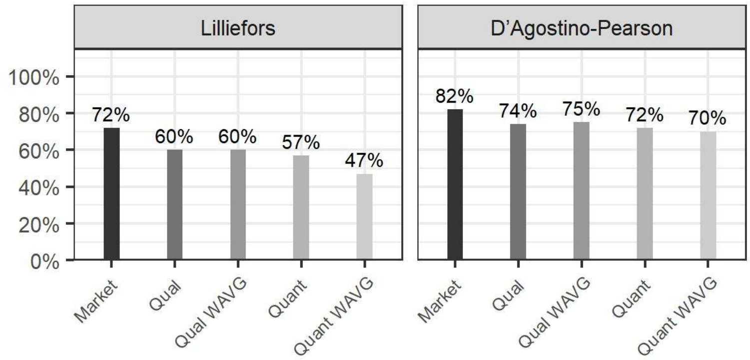

Fig. 6.10. The percentage of windows, as well as the percentage of windows weighted by total net assets (TNA), in the entire research period from 01/01/2000 to 31/12/2020, for which the Lilliefors and D'Agostino-Pearson tests for normality indicated weak-form informational efficiency. Source: Author's own study

The results provided by the normality tests constitute a basis for drawing almost completely different conclusions compared to the ones drawn on the basis of the results of the MDH tests. According to the results of the normality tests, quantitative portfolio management process gives no advantage over the traditional approaches to portfolio management in terms of the weak-form informational efficiency. Moreover, quantitative portfolio management can even harm weak-form informational efficiency. Quant funds managing larger TNA use quantitative portfolio management processes that can even more often negatively affect weak-form informational efficiency. However, since the normality tests are not suited well to the characteristics of the distributions of financial time series, the results provided by this group of tests, in the context of the examination of the weak-form efficiency, should be treated with a certain degree of caution.

The results presented in Figure 6.11. are also surprising, as the percentage of efficiency cases commonly falls across the categories not only in the period related to the global financial crisis but also after the post-crisis recovery, i.e., in the windows ending in 2018-2020. After the post-crisis recovery, all categories reached the lowest levels of efficiency in the window ending in 2020. This severe plunge in efficiency may have something in common with the coronavirus outbreak. However, it began in 2020 and the efficiency started to plunge already in the window ending in 2018.

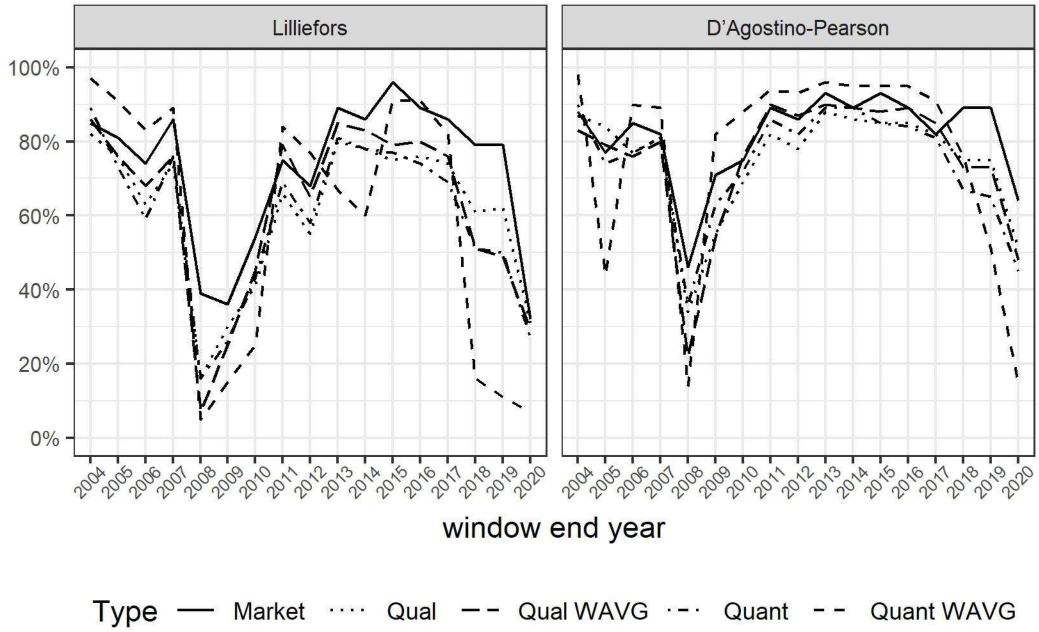

Fig. 6.11. The percentage of windows (windows tested percentage), as well as the percentage of windows weighted by total net assets (TNA), in each time window, for which the Lilliefors and D'Agostino-Pearson tests for normality indicated weak-form informational efficiency. Source: Author's own study

Some studies like the ones by Dias, Heliodoro, Alexandre, and Silva (2020), Dias et al. (2020) and Lalwani and Meshram (2020) suggest that the coronavirus outbreak had a negative impact on the weak-form informational efficiency of equity markets. A negative effect on the weak-form efficiency of equity markets was also proposed by some of the foregoing studies in the case of the global financial crisis. However, the effect of the global financial crisis was clearly visible in this study in the case of the results of both MDH and normality tests. Any possible effects of the pandemic outbreak may be visible only in the case of normality tests. Moreover, the fact that the efficiency had already started to fall before the coronavirus outbreak is still puzzling.

Moving back to the plunge of efficiency, which was most likely related to the global financial crisis, in the case of normality tests, the lowest levels of efficiency can be observed in the majority of cases in the window ending in 2008, i.e., not as in the cease of the MDH tests, in the window ending in 2009. In the case of normality tests, quant funds managing larger TNA suffered the most severely in the case of both aforementioned plunges.

The same as in the case of the results of the MDH tests, the trends of the results of normality tests were similar across different categories. This may suggest that all fund categories examined are not immune to equity market shocks and are similarly affected by them.

Figure 6.12. presents the results of normality tests only for windows ending in 2008 and 2020, i.e., windows affected by weak-form inefficiency the most. The results presented in Figure 6.12. suggest that all fund categories were inefficient more often than the market. Funds managing larger TNA tended to be inefficient even more often, especially the quant ones.

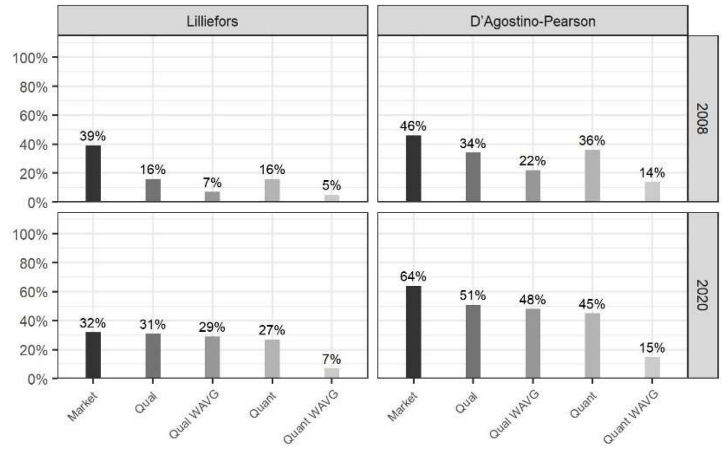

Fig. 6.12. The percentage of windows, as well as the percentage of windows weighted by total net assets (TNA), in windows ending in 2008 and 2020, i.e., in windows affected by weak-form inefficiency the most, for which the automatic Lilliefors and D'Agostino-Pearson tests for normality indicated weak-form informational efficiency. Source: Author's own study

The results of normality tests partially resemble the results of the automatic variance ratio test (Figure 6.5.). Nevertheless, there is a major difference between them, namely, in the case of normality tests, markets are more efficient than any other fund category. The biggest similarity is that the TNA-weighted quant fund category had the lowest efficiency among all fund categories. Larger quant funds in terms of managed TNA suffered especially severely in both examined windows. Bearing this in mind, larger quant funds seem to be especially fragile to market shocks in terms of the weak-form informational efficiency. In the case of qualitative funds, larger funds in terms of managed TNA also suffered more compared to smaller funds. However, a negative effect of the global financial crisis on the efficiency of larger funds was lower in the group of qualitative funds compared to the group of quantitative finds.

Table 6.7. makes an attempt to summarise the results presented in Figure 6.11. The results of the pairwise comparison of the results of normality tests presented in Table 6.7. suggest that qualitative and quantitative funds (Qual and Quant) rarely were more efficient than the markets. Funds with larger TNA were more successful in this respect, especially the quant ones. Taking into account the not-weighted categories, quant funds were more frequently more efficient compared to qualitative funds. Quant funds managing larger TNA had better results in this matter. These results may be surprising taking into account that the results presented in Figure 6.10. and Figure 6.12. suggested that quant funds and especially those with larger TNA were less efficient than qualitative funds and the market. This may suggest that the efficiency of quant funds suffers severely during the periods of instability on the equity markets and does great in remaining periods.

Normality tests - Overall results					
	Losers				
Group	Market	Qual	Qual_WAVG	Quant	Quant_WAVG
Market		0.94	0.74	0.91	0.44
Qual	0.03		0.41	0.41	0.35
Qual_WAVG	0.21	0.56		0.65	0.35
Quant	0.06	0.44	0.26		0.35
Quant_WAVG	0.56	0.65	0.65	0.65	

Tab. 6.7. The results of the pairwise comparison that indicate the percentage of cases (time windows) in which one group (rows) was more weak-form informationally efficient than another one (columns) according to both normality tests. Source: Author's own study

Results by strategy

This section tries to answer a supplementary research question of whether differences in the weak-form informational efficiency between quantitative and qualitative funds differ between the groups of funds distinguished in terms of strategy. The results broken down to selected four main strategies according to the Lipper Global Classification scheme are presented in Figure 6.13. The results differ between strategies, nevertheless, they share some common features as well. In the case of almost all distinguished groups and tests, the markets were more frequently efficient than any other fund category. The opposite was true in the case of the results of the MDH tests, except for the results obtained for hedge funds. In the case of absolute return and hedge funds, quant and qual funds with larger TNA were more frequently efficient. In most cases, the TNA-weighted quant fund category was the most efficient of all fund categories (mostly the same could be observed in the results of the MDH tests). The opposite can be observed in the case of equity funds that contribute to the majority of funds in the overall sample. In the group of equity funds, all fund categories are similarly efficient except for the TNA-weighted quant fund category, which is significantly less efficient. Is suggests that larger quant funds had lower efficiency compared to smaller quant funds. Surprisingly, in the case of the results of the MDH tests, in the group of equity funds, the TNA-weighted quant fund category delivered the highest percentage of efficient cases.

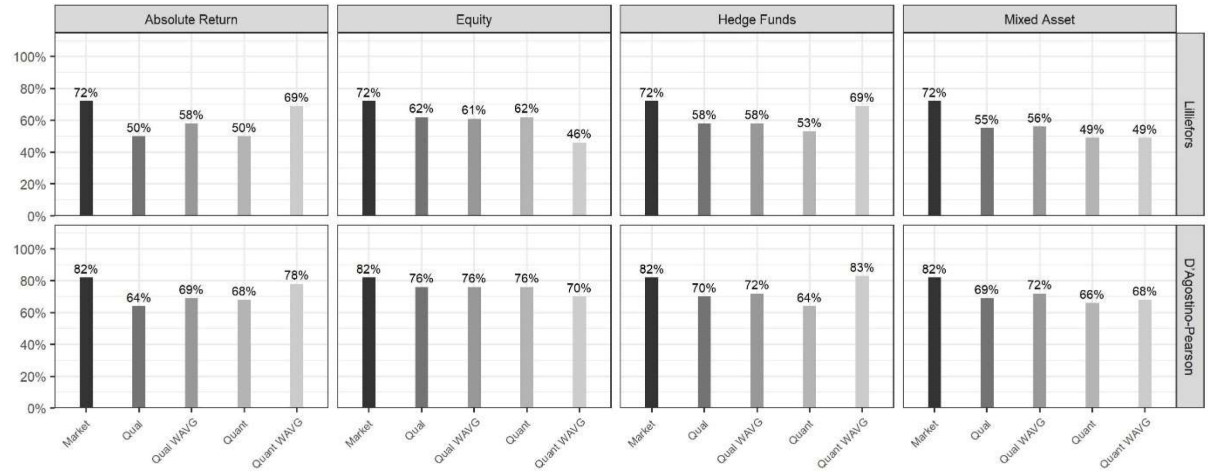

Fig. 6.13. The percentage of windows (windows tested percentage), as well as the percentage of windows weighted by total net assets (TNA) in the entire research period from 01/01/2000 to 31/12/2020, for which the Lilliefors and D'Agostino-Pearson tests for normality indicated weak-form informational efficiency, divided into selected four main strategies according to the LGC scheme. Source: Author's own study

The same as in the case of the results of the MDH tests, in the group of absolute return and hedge funds, the TNA-weighted quant fund category was the most efficient of all fund categories. Sophisticated strategies utilized by absolute return and hedge funds are especially suitable for the implementation of the quantitative portfolio management process. Surprisingly, the implementation of quant techniques in the case of equity funds managing larger TNA failed miserably, resulting in the lowest percentage of efficient cases in the case of TNA-weighted quant fund category.

Concerning the behaviour of efficiency across time windows, according to Figure 6.14., only in the most numerous groups, i.e., in the group of equity funds and mixed asset funds, the trends of the efficiency for the majority of categories were clearly similar to those of the overall sample. However, most of the fund categories across the examined strategies shared a common feature that consisted in the drop of efficiency in periods related to the global financial crisis and especially in the windows ending in 2018-2020.

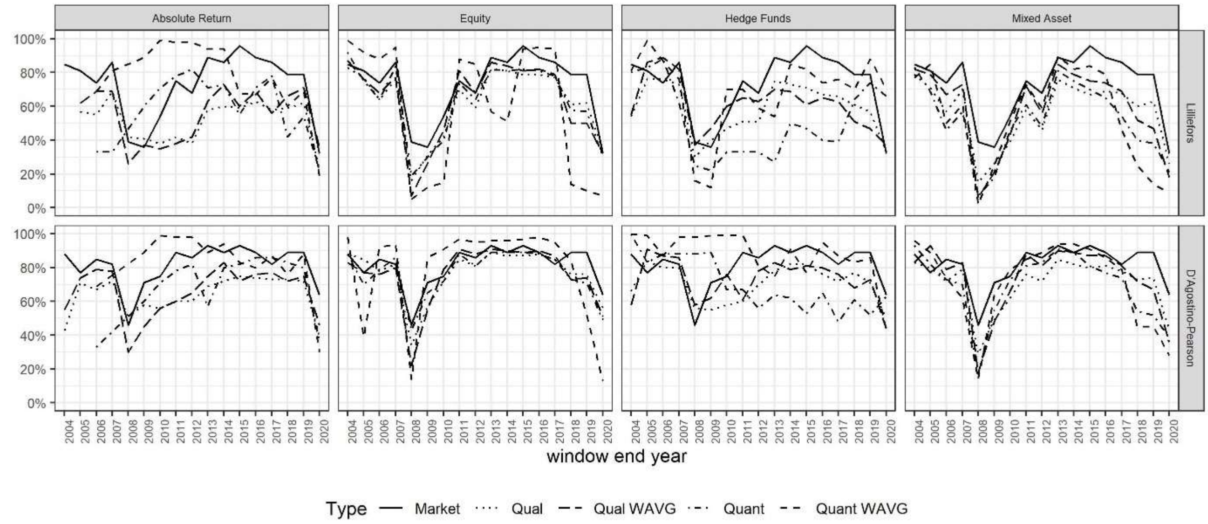

Fig. 6.14. The percentage of windows (windows tested percentage), as well as the percentage of windows weighted by total net assets (TNA) in each time window, for which the Lilliefors and D'Agostino-Pearson tests for normality indicated weak-form informational efficiency, divided into selected four main strategies according to the LGC scheme. Source: Author's own study

Table 6.8. constituting an attempt to summarise the results presented in Figure 6.14. suggests that all fund categories were rarely more efficient than the market. However, it should be noted that quant funds did better in this matter, especially the larger ones in terms of TNA managed. Quant funds more often exceeded qualitative funds in terms of efficiency in the groups of absolute return and equity funds. The opposite was true in the case of hedge funds. In the group of mixed asset funds, none of the fund categories managed to get a clear advantage. The results presented in Figure 6.14. do not differ much from the ones delivered by the MDH tests, except for the results for funds in comparison to the market, which was more often exceed by them, and especially quant funds, in the MDH tests.

Normality tests - Absolute Return

	Losers				
Group	Market	Qual	Qual_WAVG	Quant	Quant_WAVG
Market		0.91	0.94	0.81	0.56
Qual	0.09		0.27	0.33	0.07
Qual_WAVG	0.06	0.64		0.37	0.22
Quant	0.19	0.67	0.59		0.22
Quant_WAVG	0.44	0.93	0.74	0.78	

Normality tests - Equity

	Losers				
Group	Market	Qual	Qual_WAVG	Quant	Quant_WAVG
Market		0.85	0.68	0.85	0.41
Qual	0.09		0.44	0.29	0.35
Qual_WAVG	0.24	0.56		0.59	0.35
Quant	0.09	0.44	0.35		0.35
Quant_WAVG	0.59	0.65	0.65	0.65	

Normality tests - Hedge Funds

	Losers				
Group	Market	Qual	Qual_WAVG	Quant	Quant_WAVG
Market		0.85	0.71	0.74	0.53
Qual	0.15		0.35	0.59	0.18
Qual_WAVG	0.29	0.65		0.68	0.26
Quant	0.26	0.41	0.32		0.15
Quant_WAVG	0.47	0.82	0.71	0.82	

Normality tests - Mixed Asset

	Losers				
Group	Market	Qual	Qual_WAVG	Quant	Quant_WAVG
Market		0.97	0.91	0.91	0.76
Qual	0.03		0.29	0.5	0.41
Qual_WAVG	0.06	0.68		0.68	0.53
Quant	0.06	0.5	0.29		0.32
Quant_WAVG	0.24	0.59	0.47	0.68	

Tab. 6.8. The results of the pairwise comparison that indicate the percentage of cases (time windows) in which one group (rows) was more weak-form informationally efficient than another one (columns) according to both normality tests, divided into selected four main strategies according to the LGC scheme. Source: Author's own study

Results by region

This section tries to answer a supplementary research question of whether differences in the weak-form informational efficiency between quantitative and qualitative funds differ between the groups of funds distinguished in terms of the region of a primary investment focus. Moving onto a breakdown of the results into the geographic regions of a primary investment focus presented in Figure 6.15., in the groups of funds primarily investing in the region of Eastern Asia and Western Europe, the funds with the larger TNA were more often efficient, without any more significant differences between the qualitative and quantitative funds. In the group of funds primarily investing in Northern Europe, the opposite appears to be true. In this group, quantitative funds appear to be efficient more frequently compared to qualitative funds. A group of funds primarily investing in Northern America seems to have the worst results across all fund categories. Quantitative funds seem to have the worst results, especially those with larger TNA. The results received for Northern America seem to resemble the overall results the most, most likely due to their largest share in the overall sample. To sum up, the results presented in Figure 6.15. show many differences compared to the results of the MDH tests. They also vary across the regions.

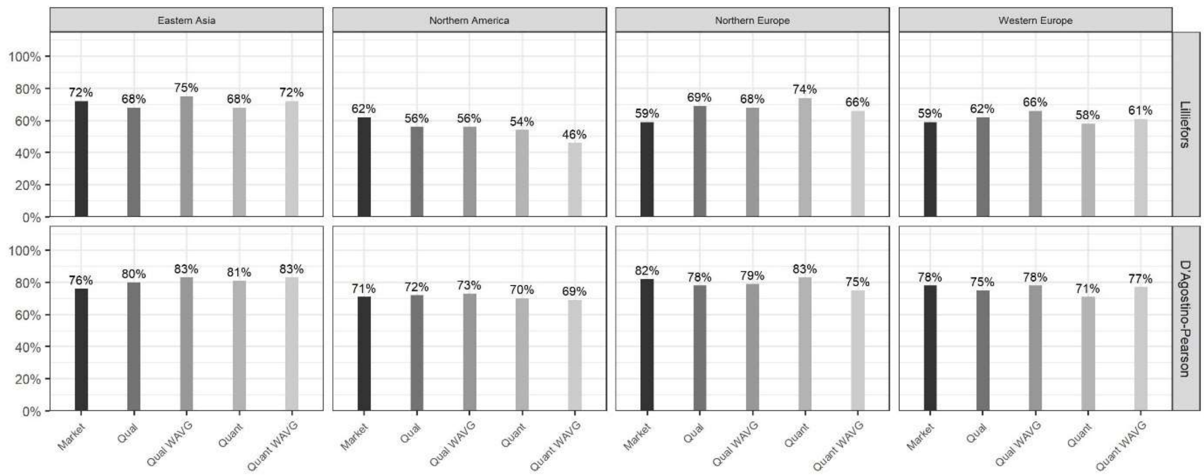

Fig. 6.15. The percentage of windows (windows tested percentage), as well as the percentage of windows weighted by total net assets (TNA) in the entire research period from 01/01/2000 to 31/12/2020, for which the Lilliefors and D'Agostino-Pearson tests for normality indicated weak-form informational efficiency, divided into four most numerous regions of a primary investment focus. Source: Author's own study

Figure 6.16. presents the results of normality tests broken down to four most numerous regions of a primary investment focus across all time windows. The same as in the case of Figure 6.9., which presents the analogical results but for the MDH tests, no results for the market are presented due to a small size of the sample. A pattern, which was observable in the case of the overall sample, is also observable across all examined regions, namely, a plunge of efficiency up to the window ending in 2008, a following recovery, and then a plunge of efficiency again from the window ending in 2018.

The efficiency of quant and qual funds behaves more or less similarly in particular regions over the time windows. A similar conclusion could also be drawn from the analysis of the results of the MDH tests. It suggests that in terms of the weak-form informational efficiency, quant and qual funds have much in common. The application of a quantitative investment process may not change diametrically the behaviour of the efficiency of investment funds.

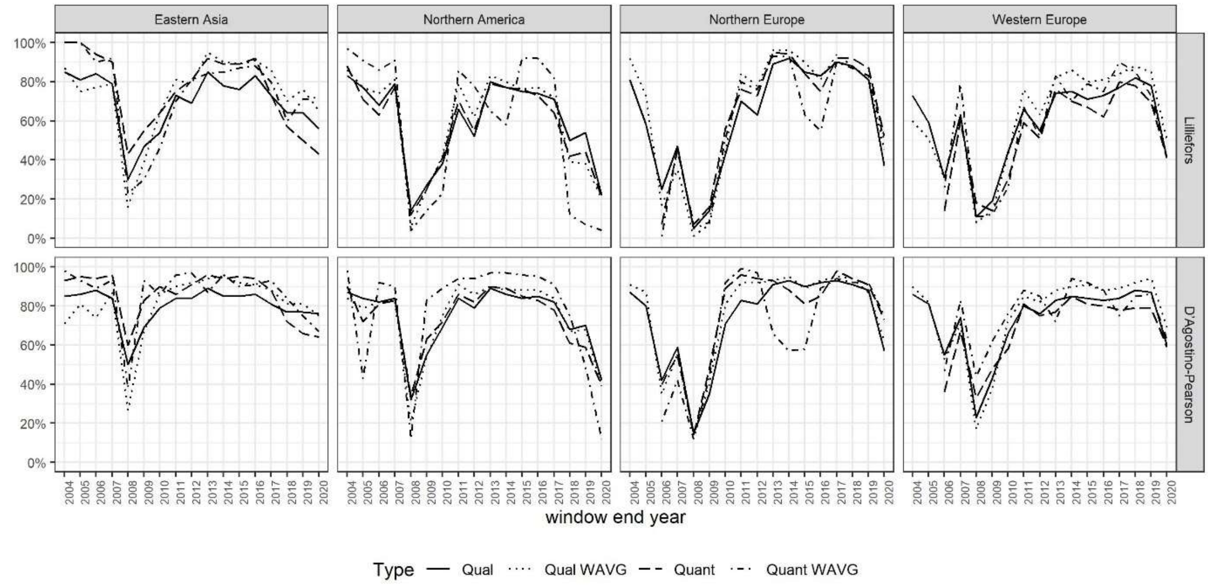

Fig. 6.16. The percentage of windows (windows tested percentage), as well as the percentage of windows weighted by total net assets (TNA) in each time window, for which the Lilliefors and D'Agostino-Pearson tests for normality indicated weak-form informational efficiency, divided into four most numerous regions of a primary investment focus. Source: Author's own study

Table 6.9., which makes an attempt to summarise the results presented in Figure 6.16., suggests that when comparing basic fund categories (Quant and Qual), in the group of Eastern Asia and Northern Europe, the efficiency of quant funds more often exceeded the efficiency of qualitative funds. The opposite was true in the case of the two remaining regions. In addition, in the groups of Eastern Asia and Northern Europe, larger quant funds in terms of TNA tended to be more frequently efficient compared to qualitative funds. The opposite was true in the case of the two remaining regions. When it comes to the comparison of the results delivered by the MDH and normality tests, only in the case of the group of funds primarily investing in Northern America, the results were similar.

Normality tests - Eastern Asia				
	Losers			
Group	Qual	Qual_WAVG	Quant	Quant_WAVG
Qual		0.29	0.18	0.29
Qual_WAVG	0.68		0.38	0.41
Quant	0.79	0.53		0.5
Quant_WAVG	0.71	0.53	0.41	

Normality tests - Northern America				
	Losers			
Group	Qual	Qual_WAVG	Quant	Quant_WAVG
Qual		0.38	0.56	0.35
Qual_WAVG	0.56		0.59	0.35
Quant	0.41	0.26		0.35
Quant_WAVG	0.65	0.65	0.65	

Normality tests - Northern Europe				
	Losers			
Group	Qual	Qual_WAVG	Quant	Quant_WAVG
Qual		0.26	0.33	0.4
Qual_WAVG	0.65		0.4	0.6
Quant	0.67	0.5		0.7
Quant_WAVG	0.5	0.4	0.3	

Normality tests - Western Europe				
	Losers			
Group	Qual	Qual_WAVG	Quant	Quant_WAVG
Qual		0.26	0.73	0.37
Qual_WAVG	0.68		0.87	0.57
Quant	0.2	0.1		0.17
Quant_WAVG	0.57	0.4	0.77	

Tab. 6.9. The results of the pairwise comparison that indicate the percentage of cases (time windows) in which one group (rows) was more weak-form informationally efficient than another one (columns) according to both normality tests, divided into four most numerous regions of a primary investment focus. Source: Author's own study

6.4. Conclusions

As already turned out in a discussion on the results obtained for the overall sample, both groups of the applied weak-form informational efficiency tests provided ambiguous results. Even between the MDH tests (the automatic Portmanteau test for serial correlation and the wild bootstrapped automatic variance ratio test under conditional heteroskedasticity), a certain degree of the lack of unambiguousness could be observed as well. This looked much better in the case of the applied normality tests, namely the Lilliefors test and the D'Agostino-Pearson test. The indications of the results of both normality tests were more consistent compared to those of the MDH tests.

Taking into account the results of the MDH tests for the overall sample, which show the percentage of efficient windows in the entire research period, all fund categories had similar or higher results compared to the market. The percentage of efficient cases in all categories was high, reaching at least 80%. The results across the fund categories were also similar except for the results for the TNA-weighted quant funds that positively outstood. Such results may suggest that larger quant funds in terms of managed TNA were more efficient compared to smaller quant funds. A higher percentage of efficient cases may be related to the application of more developed quantitative portfolio management process compared to smaller quant funds. A development of a more advanced quantitative portfolio management process requires to devote greater capital expenditures, and it is more likely that larger quant funds can afford this. A more advanced quantitative portfolio management process may positively affect informational efficiency, for instance, by limiting some behavioural errors, applying some more reliable investment strategies, or diversifying the portfolio in a better way.

Surprisingly, the results of the normality tests turned out to be much different. They allowed to draw almost entirely opposite conclusions. None of the fund categories was more often efficient than the market. Quant funds were less efficient compared to the qual ones, and the larger quant funds in terms of TNA were especially worse in this matter. The dominance of the market in terms of the results of normality tests may come from a diversification of stock market indices that can be treated as portfolios. According to the central limit theorem, the distribution of the returns of a well-diversified portfolio should be similar to a normal distribution (Zamojska, 2012).

The differences between the MDH and normality tests result from their construction and assumptions. As opposed to the MDH tests, the normality tests are not that much suitable for financial time series due to very strict assumptions. Due to this and substantial differences in results, the author of this study proposes to approach the results of normality tests with a certain degree of caution.

The behaviour of the efficiency of the categories examined across the windows suggests that the efficiency of the stock markets, quantitative funds, and qualitative funds behaved similarly across the strategies and regions examined. It suggests that regardless of different strategies and regions, quant funds, qual funds, and equity markets are related in terms of the weak-form informational efficiency. Moreover, their efficiency could have been negatively and similarly affected by market shocks such as the global financial crisis. The results of the MDH and normality tests indicated a decrease in the percentage of efficient cases in periods related to the global financial crisis. After the aforementioned decrease, a recovery to pre-crisis efficiency levels took place. This pattern could be observed in the case of the majority of categories across the examined strategies and regions. Furthermore, according to the results of normality tests, after the post-crisis recovery, the efficiency started to plunge again from about the window ending in 2018. In many cases, efficiency reached the lowest levels in the window ending in 2020 since the last plunge that was most likely related to the global financial crisis. This severe decrease in efficiency may have something in common with the coronavirus outbreak. However, the coronavirus outbreak began in 2020, and the efficiency started to plunge already in the window ending in 2018. The fact that the MDH tests did not show any plunge in these windows is also puzzling.

When considering the results obtained for the entire sample across the windows, quant funds appeared to be more frequently more efficient compared to qualitative funds. Nevertheless, the advantage of quantitative funds was not that substantially frequent. At the level of individual groups distinguished in terms of the applied strategy, a similar situation could be observed in the groups of absolute return and equity funds. When it comes to the other two strategies, the situation was not so clear, as the results obtained by the two types of tests were highly inconsistent. However, according to the MDH tests, which are more preferable, the advantage of quant funds in terms of efficiency was visibly more often. When it comes to groups distinguished in terms of the region of a primary investment focus, the MDH and normality tests provided results that allowed to draw consistent conclusions only in the case of two groups, namely, funds primarily investing in Northern Europe and Northern America. In the case of funds primarily investing in Northern America, qualitative funds were more efficient clearly more often. On the other hand, in the case of funds primarily investing in Northern Europe, quantitative funds were more efficient slightly more often. In the other two groups, the results of the two groups of tests were highly ambiguous. Nevertheless, according to the MDH tests, in the group of Eastern Asia, quantitative funds had lower efficiency in the majority of windows. The opposite was true in the case of the group of funds primarily investing in Western Europe.

The advantage of quantitative funds over qualitative funds could be observed at the level of a whole sample and individual groups distinguished in terms of the applied strategy. However, just in the case of few groups, this advantage was clearly systematic. At the level of particular groups distinguished in terms of the region of a primary investment focus, the situation looked quite different, as in the case of some samples, qualitative funds had more systematic advantage over quantitative funds. Thus, the results obtained in the first part of the study do not unambiguously suggest rejecting the H2 hypothesis.

The first part of the study also provided many interesting conclusions that constituted the answers to supplementary research questions posed in the introduction. The results of the first part of the study suggest that the differences in the weak-form informational efficiency between quantitative and qualitative funds differed between the groups of funds distinguished in terms of strategy and the region of a primary investment focus.

What is more, according to the results of the first part of the study, larger quantitative funds in terms of TNA appeared to be more frequently more efficient than smaller quantitative funds in almost all the examined groups. The most systematic advantage of larger quantitative funds over the smaller ones could be observed in a whole sample, a sample of equity funds and a sample of funds primarily investing in Northern America. Larger funds in terms of TNA turned out to be more frequently more efficiency also in the group of qualitative funds. Nevertheless, a discussed phenomenon was stronger in the case of quantitative funds.

Referring to differences in informational efficiency between quantitative funds and their relevant equity market benchmarks, quantitative funds did not manage to gain any clear advantage over the market. It pertained to any examined group. Moreover, according to the results of the MDH tests, the efficiency of quantitative funds was lower compared to the efficiency of the markets in the great majority of cases in the groups of absolute return and hedge funds. According to the indications of normality tests, quantitative funds had a lower efficiency compared to equity markets in the vast majority of time windows in all examined groups. However, it is worth mentioning that qualitative funds were found to be even slightly worse than quantitative funds in terms of differences in informational efficiency between them and their relevant equity market benchmarks. The differences in informational efficiency between quantitative funds and their relevant equity market benchmarks across the groups distinguished in terms of the region of a primary investment focus were not examined due to a small number of the markets in each region.

The results of the MDH tests indicated the window ending in 2009 as the window of the lowest levels of equity market efficiency. The windows ending in 2008 and 2020 were indicated as the windows of the lowest levels of equity market efficiency by the results of normality tests. Regarding the differences in efficiency between quantitative and qualitative funds in periods of low efficiency of equity markets, when comparing the results obtained for the non-weighted fund categories, none of the applied tests suggested any significant differences between quantitative and qualitative funds. However, when taking into account the TNA-weighted categories, larger funds turned out to be less efficient, especially in the quant fund group. Nevertheless, this observation was not confirmed by the indication of the automatic Portmanteau test. Thus, the results suggest that in periods of the lowest levels of equity market efficiency, some substantial differences in efficiency between quantitative and qualitative funds were observable after accounting for TNA. Larger funds in terms of TNA were less efficient in both quantitative and qualitative funds. However, especially larger quantitative funds were worse in this matter.

Furthermore, the weak-form efficiency study provided information on the normality of the distribution of fund returns, which is essential in terms of the application of some performance measures that require the normality of returns. Taking into account the results of the normality tests for the overall sample, which show the percentage of efficient windows in the entire research period, in the majority of cases, the analysed time series were normally distributed. However, a fraction of time series that were not normally distributed was still significant. Moreover, in some periods, a percentage of normally distributed time series was clearly scarce. The low percentages of normally distributed time series could be observed especially in the windows related to the global financial crisis and in the windows ending after 2017. In terms of the application of some performance measures that require the normality of returns, the indications of performance results in Chapter 7 will be very important. If the application of any performance measure is not justified, measures that require normally distributed time series will likely provide results that allow for stating different conclusions compared to measures robust to the non-normality of returns.

7. The results of the study on the performance of quantitative funds with the use of relative measures of portfolio performance as well as raw and excess returns - the second part of the study

This chapter discusses the results of the second part of the study, i.e., the one concerning the performance of quantitative funds with the use of relative measures of portfolio performance as well as raw and excess returns. The main research objective of this part of the study is to answer a fundamental question of whether the performance of quantitative funds is higher than the performance of qualitative funds. In addition, this chapter aims to answer the question of whether quantitative funds perform better than qualitative funds in periods of low weak-form informational efficiency of the equity markets.

The second part of the study uses the same rolling window methodology with the same parameters as the first part of the study (presented in Section 6.1.). Thus, also the final sample is identical. The average results obtained for different portfolio performance measures are presented and discussed in Sections 7.1.–7.5. Each of these sections refers to a different group of performance measures. The split of the applied performance measures into the different groups was discussed in Section 5.3.2. Additionally, following Harvey et al. (2017), a comparative analysis of the average results obtained for different portfolio performance measures is supplemented with a comparative analysis of homogeneity of the average results in the groups of quantitative and qualitative funds. Section 7.6. presents the results of the study on the performance of quantitative funds in periods of low weak-form informational efficiency of the equity markets. These periods were selected in the study on the weak-form informational efficiency of quantitative funds discussed in Chapter 6. Following Harvey et al. (2017), the examination of the performance of quantitative funds will be supplemented with the examination of the Pearson correlation coefficients between the raw returns of quantitative funds and qualitative funds in Section 7.7. The results discussed in Sections 7.1.–7.7. will be concluded in Section 7.8.

7.1. Raw and excess returns

Overall results

Figure 7.1. presents the average monthly raw and excess returns, as well as the average monthly raw and excess returns weighted by TNA, calculated for all rolling windows in the entire research period from 01/01/2000 to 31/12/2020. The results presented in Figure 7.1. indicate that when it comes to raw returns, none of the fund categories managed to outperform the market. However, the results obtained for the TNA-weighted quant fund category were close to the results of the market. They were also clearly higher compared to the results of the other fund categories, which were marked by a similar average performance. It may suggest that larger quant funds outperformed smaller quant funds and the majority of qualitative funds. In the case of the average excess returns, the results obtained for the TNA-weighted quant fund category outstood even more. Other fund categories had a similar level of performance also in

this case. The major difference between the results of excess and raw returns was that the difference between the market and other fund categories diminished.

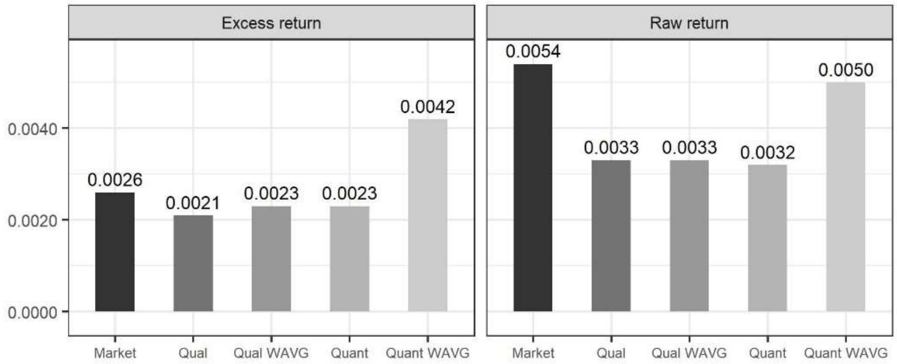

Fig. 7.1. The average monthly raw and excess returns calculated for all rolling windows of the market (Market), qualitative funds (Qual), and quantitative funds (Quant), as well as the average monthly raw and excess returns weighted by the total net assets of qualitative funds (Qual WAVG) and quantitative funds (Quant WAVG), calculated for all rolling windows in the entire research period from 01/01/2000 to 31/12/2020. Source: Author's own study

The results received suggest that when it comes to performance generated, there may be some significant differences between the quantitative portfolio management processes applied by smaller and larger quant funds in terms of TNA managed. Such significant differences cannot be observed in the case of qualitative funds, which suggests that larger TNA managed does not necessarily help to implement more profitable traditional portfolio management process. Larger quant funds in terms of managed TNA may apply more advanced quantitative portfolio management processes capable of generating better performance. The advantage of the these processes may result from the size of larger quant funds (in terms of TNA) and thus, a better possibility to devote greater capital expenditures for development of quantitative portfolio management processes. However, in terms of raw returns, even the advanced quantitative portfolio management processes did not help the quant funds outperform the market. Their advantage appeared after accounting for the risk-free rate.

Taking into account simple averages (the results for categories marked as Quant and Qual), quantitative portfolio management processes applied by the quant funds allow for generating performance at the level of performance generated by qualitative funds. It may suggest that the quantitative portfolio management processes they apply do not allow them to gain advantage over human managers in terms of the average performance generated. These results partially are not in line with the ones proposed in the study by Chuang and Kuan (2018). According to them, quant funds outperformed qualitative ones in terms of the raw returns. Nevertheless, after accounting for TNA, quant funds appeared to outperform the qualitative ones at is was discussed earlier. It should also be remembered that Chuang and Kuan (2018) focused only on hedge funds.

Following Harvey et al. (2017) who wanted to verify if discretionary and systematic funds (as they called them) were similarly homogeneous, the 25th and 75th percentiles of the average monthly raw and excess returns, as well as spreads between these percentiles, were calculated for all rolling windows of qualitative (Qual) and quantitative (Quant) funds in the entire research period from 01/01/2000 to 31/12/2020. The results of these calculations are presented in Figure 7.2. According to the results presented in Figure 7.2., the percentiles and spreads of the compared fund types were at similar levels in the case of both measures. Thus, quantitative and qualitative funds can be considered similarly homogeneous in terms of performance measured with average monthly raw and excess returns. These results are in line with those of Harvey et al. (2017).

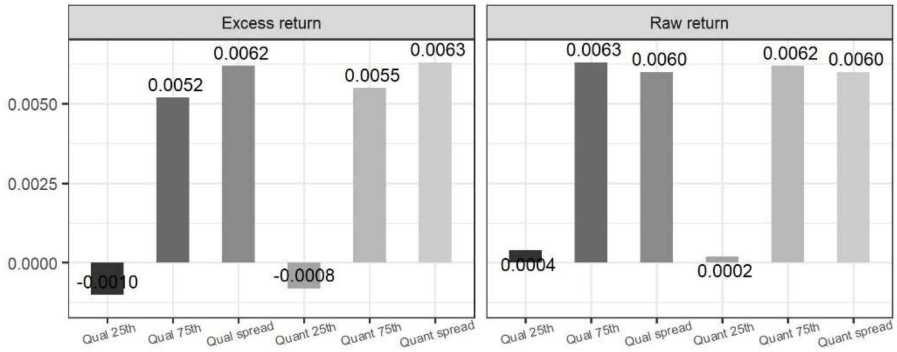

Fig. 7.2. The 25th and 75th percentile of the average monthly raw and excess returns, as well as spread between these percentiles, calculated for all rolling windows of qualitative (Qual) and quantitative (Quant) funds in the entire research period from 01/01/2000 to 31/12/2020. Source: Author's own study

Figure 7.3. presents the average monthly raw and excess returns, as well as the average monthly raw and excess returns weighted by TNA, calculated separately for each time window. Referring to Figure 7.3., up to the window ending in 2013 all fund categories seem to have similar performance. Then, quant funds managing larger TNA started to outperform other funds. This puzzling issue may be explained with a recent development of technology, which enabled especially larger quant funds (in terms of TNA they manage) to develop more profitable strategies. Nevertheless, when considering simple average results for quant and qual funds, their performance was similar over all examined time windows suggesting positive and at least moderate correlations between them. This, in turn, suggests the similarity of strategies they apply in terms of performance generated. Correlations between returns generated by quant and qual funds will be additionally discussed in Section 7.7.

In the case of excess returns, the market systematically outperformed all fund categories by the window ending in 2011. Then the situation changed and the market was outperformed by funds in the majority of cases. In the case of raw returns, a systematic outperformance of funds by the market was observable by the window ending in 2012. Up to this window, the levels of the performance of the market were not that much similar to the levels of the performance of funds. In the following windows it changed, and the results suggest that strategies applied by the examined funds were much more similar to the market in terms of performance generated.

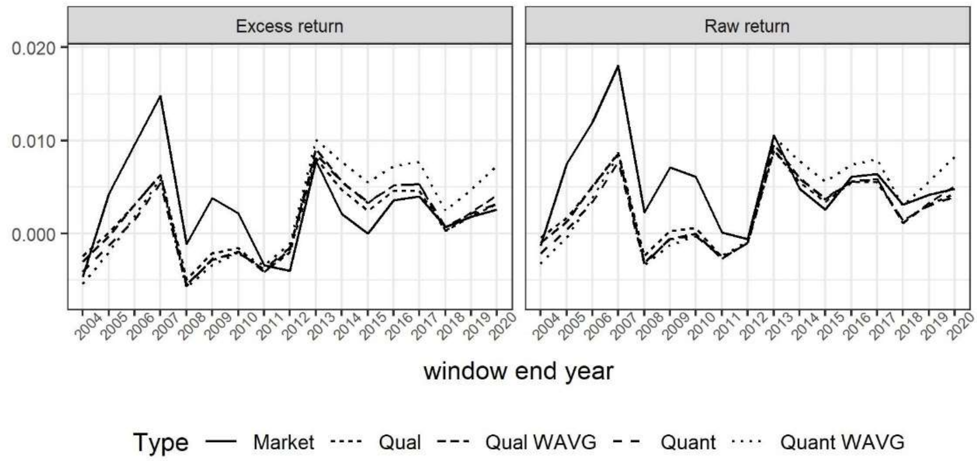

Fig. 7.3. The average monthly raw and excess returns in each time window, calculated for the markets (Market), qualitative funds (Qual), and quantitative funds (Quant), as well as the average monthly raw and excess returns in each time window weighted by the total net assets of qualitative (Qual WAVG) and quantitative (Quant WAVG) funds. Source: Author's own study

It is also worth noting that after the first four windows of a constant increase of raw and excess returns in the case of all categories analysed, a significant drop came in the window ending in 2008. For almost all fund categories in the case of both discussed measures, the average performance in the window ending in 2008 was the lowest among all windows. This issue can most likely be related to the global financial crisis. Nevertheless, the performance of equity markets was even lower in the window ending in 2012 than in the window ending in 2008, which is concerning in this situation.

Table 7.1. makes an attempt to summarise the average performance from all windows presented in Figure 7.3. by presenting the results of a pairwise comparison that indicate the percentage of cases (time windows) in which one group (rows) performed better than another one (columns) according to both average raw and excess returns. The sum of the win rates of two compared categories does not have to equal one, as there could have been a draw in some windows. The same method of the presentation of results has already been used in Section 6.2. and Table 7.1. needs to be interpreted in a similar way as explained in the examples of the interpretation of results presented in Table 6.4. in Section 6.2.

Raw and excess returns - Overall results

	Losers				
Group	Market	Qual	Qual_WAVG	Quant	Quant_WAVG
Market		0.65	0.62	0.65	0.53
Qual	0.35		0.38	0.53	0.41
Qual_WAVG	0.38	0.47		0.65	0.41
Quant	0.32	0.38	0.26		0.26
Quant_WAVG	0.44	0.59	0.59	0.74	

Tab. 7.1. The results of a pairwise comparison that indicate the percentage of cases (time windows) in which one group (rows) performed better than another one (columns) according to both average raw and excess returns. Source: Author's own study

Referring to the results of a pairwise comparison presented in Table 7.1., qualitative and quantitative funds appeared to outperform the market much less frequently. Funds managing larger TNA (especially the quant ones) did it more often. Nevertheless, the market outperformed all fund categories more frequently. Considering simple averages of performance measures, qualitative funds outperformed quant funds more frequently. However, the opposite was true when taking into account TNA-weighted results.

As the results presented in Figure 7.1. refer to the average performance across all windows, Table 7.1. indicates how often one category had a better result compared to the another one. Also, in the case of the results presented in Table 7.1., the TNA-weighted quant fund category managed to dominate other fund categories in the majority of cases. It indicates that the positively outstanding average raw and excess returns of the category of TNA-weighted quants (Figure 7.1.) did not result from just a few outstanding windows but were instead a repeating phenomenon. It also suggests that the quantitative portfolio management processes used by larger quants in terms of managed TNA enabled them to generate advantage more systematically over the other funds. Referring to Figure 7.3., a systematic outperformance of the market and other fund categories by TNA-weighted quant category is clearly observable from the window ending in 2013. However, when analysing the results of the not-weighted categories, quant funds had more frequently worse performance compared to qualitative funds.

It is also worth mentioning that according to the data presented in Figure 7.1., in the group of qualitative funds, the larger funds (in terms of TNA managed) do not have such a significant advantage over the smaller funds, as is noticeable in the group of quantitative funds. It is in line with the indications of the average results for the entire research period presented in Figure 7.1. The results obtained suggest that TNA managed impact performance less positively in the group of qualitative funds compared to the group of quantitative funds.

Results by strategy

Previously discussed results obtained for the average raw and excess returns pertained to the overall sample that contained funds from different strategies and regions of a primary investment focus. Thus, it will be interesting if the analysis of the results calculated for particular strategies allows for drawing similar conclusions. This section tries to answer a supplementary research question of whether the differences in performance between quantitative and qualitative funds differ between the groups of funds distinguished in terms of strategy. Referring to Figure 7.4., the results seem to differ significantly between strategies. They seem to differ from the overall results as well. The higher average performance of both fund types (Quant and Qual) in terms of measures discussed can be attributed to equity and hedge funds. The lower average performance instead can be attributed to absolute return and mixed asset funds. However, these strategies tend to be less risky compared to equity and hedge funds and, thus, their performance was lower as well.

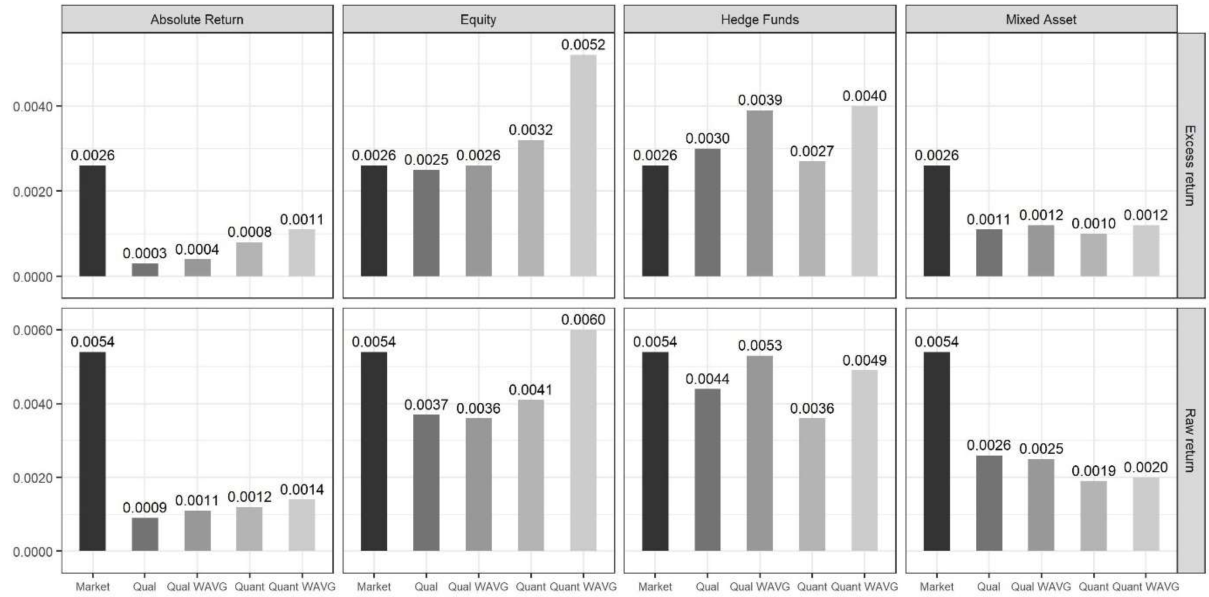

Fig. 7.4. The average monthly raw and excess returns calculated for all rolling windows of the markets (Market), qualitative funds (Qual), and quantitative funds (Quant), as well as the average monthly raw and excess returns weighted by the total net assets of qualitative (Qual WAVG) and quantitative (Quant WAVG) funds, calculated for all rolling windows in the entire research period from 01/01/2000 to 31/12/2020, divided into four selected main strategies according to the LGC scheme. Source: Author's own study

Quant funds seem to outperform qualitative funds only in the case of absolute return and equity funds. In the case of the two remaining strategies, namely, hedge and mixed asset funds, qualitative funds seem to manage slightly better. However, when accounting for the risk-free rate, the differences between them almost vanish. Across most strategies and fund types, funds managing larger TNA seem to perform better. Again, the higher performance of larger funds in terms of managed TNA may be ascribed to higher expenditures on portfolio management process development that lead to better performance. The biggest differences in terms of the impact of TNA on the weighted average performance between quantitative and qualitative funds can be observed in the group of equity funds. In this group, similarly to overall results, only in the case of quant funds, larger TNA made a clearly positive difference.

Quantitative portfolio management process seems to give the advantage to the quant absolute return funds over the qualitative absolute return funds in terms of performance. Still, quant absolute return funds cannot ensure the advantage over the market. Quant absolute return funds managing larger TNA performed even better. Nevertheless, still, they could not outperform the market, at least taking into account the average results for the sample in the entire research period. However, absolute return funds aim to outperform a risk-free or cash benchmark rather than equity market benchmark (Refinitiv, 2019). Considering equity funds, after accounting for the risk-free rate, the quantitative portfolio management process ensures the advantage to quant equity funds over qualitative funds and the market. Again, quant funds managing larger TNA did significantly better in this matter. It is also worth noting that the results obtained for the group of equity funds resemble the overall results the most. Most likely due to the largest share in the final sample.

Hedge funds are considered the most risky of all examined strategies due to less regulatory limitations they have, which in turn encourages managers to apply some more sophisticated and risky strategies. They were also considered the most interesting objects of analysis in the issue-related studies by Chincarini (2014), Harvey et al. (2017), and Chuang and Kuan (2018). Freedom and space in the application of risky and sophisticated strategies may encourage portfolio managers to implement quantitative portfolio management processes. As opposed to the general conclusions proposed in the aforementioned studies, the results presented in Figure 7.4. do not allow for stating that quant hedge funds have the advantage over qualitative funds. Taking into account the average raw returns, quant funds perform even slightly worse. However, after accounting for risk-free rate, the differences almost vanish. The same applies to mixed asset funds. Quantitative and qualitative mixed asset funds did not manage to outperform the market, neither in the case of the average raw returns nor in the case of the average excess returns. In the case of the hedge funds, after accounting for the risk-free rate, all fund categories outperformed the market.

Figure 7.5. presenting the average raw and excess returns across time windows delivers some interesting information regarding the behaviour of performance measures over time across different strategies. One of the first differences between strategies that outstands is their volatility. Absolute return funds seem to be the least volatile and the least related to the market, which is in line with their nature and goals. Nevertheless, most of the time they are outperformed by the market. On the other hand, equity funds seem to be the most volatile and the most similar to the overall sample. It is worth noting that across the examined strategies the behaviour of the performance of fund categories was similar suggesting that quant and qual returns may be positively correlated.

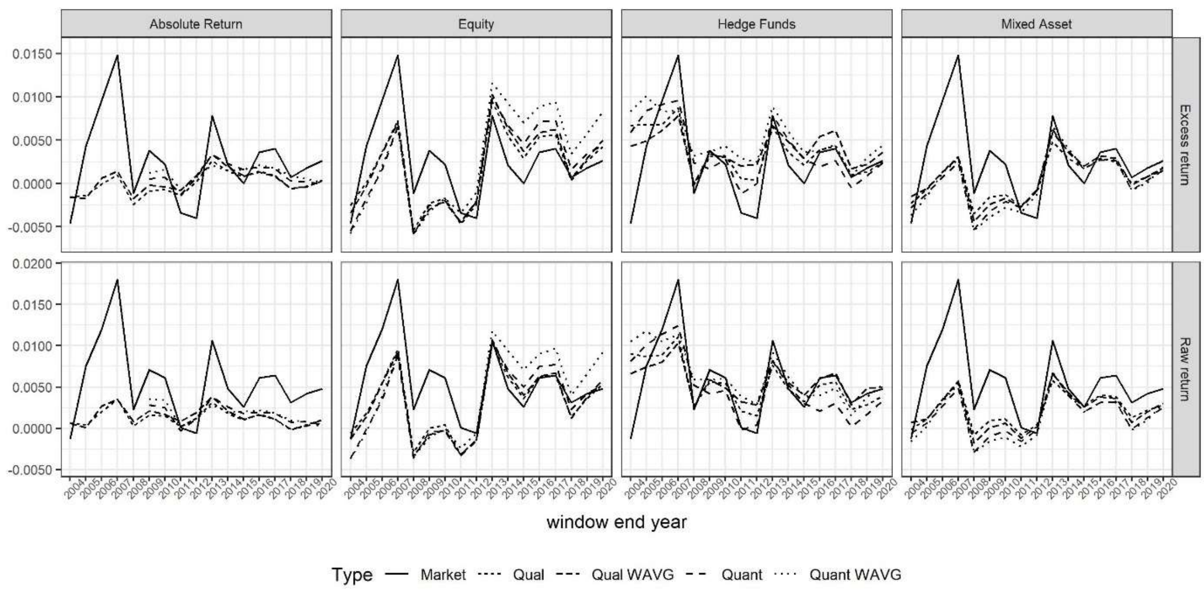

Fig. 7.5. The average monthly raw and excess returns in each time window, calculated for the markets (Market), qualitative funds (Qual), and quantitative funds (Quant), as well as the average monthly raw and excess returns weighted by the total net assets of qualitative (Qual WAVG) and quantitative (Quant WAVG) funds in each time window, divided into four selected main strategies according to the LGC scheme. Source: Author's own study

The same as in the case of the overall sample, the results for each window presented in Figure 7.5. were summarised with the use of a pairwise comparison whose outcomes are presented in Table 7.2. The results of the aforementioned pairwise comparison suggest that differences between the categories vary across strategies. In the majority of cases, funds did not manage to outperform the market more frequently. What is more, When considering the non-weighted categories, in most cases, quant funds did not manage to outperform qual funds more frequently, except for the case of absolute return funds. Nevertheless, when considering weighted funds categories, in the case of all groups except for mixed asset funds, quants managed to perform better more frequently than qual funds.

Raw and excess returns - Absolute Return

	Losers				
Group	Market	Qual	Qual_WAVG	Quant	Quant_WAVG
Market		0.79	0.79	0.79	0.75
Qual	0.21		0.21	0.12	0.17
Qual_WAVG	0.21	0.62		0.25	0.38
Quant	0.21	0.83	0.67		0.21
Quant_WAVG	0.25	0.75	0.58	0.62	

Raw and excess returns - Equity

	Losers				
Group	Market	Qual	Qual_WAVG	Quant	Quant_WAVG
Market		0.56	0.53	0.56	0.44
Qual	0.41		0.44	0.5	0.38
Qual_WAVG	0.44	0.5		0.56	0.35
Quant	0.41	0.5	0.41		0.21
Quant_WAVG	0.5	0.59	0.65	0.76	

Raw and excess returns - Hedge Funds

	Losers				
Group	Market	Qual	Qual_WAVG	Quant	Quant_WAVG
Market		0.5	0.35	0.56	0.35
Qual	0.5		0.29	0.62	0.18
Qual_WAVG	0.65	0.71		0.65	0.24
Quant	0.44	0.38	0.35		0.12
Quant_WAVG	0.65	0.82	0.74	0.88	

Raw and excess returns - Mixed Asset

	Losers				
Group	Market	Qual	Qual_WAVG	Quant	Quant_WAVG
Market		0.76	0.76	0.79	0.85
Qual	0.24		0.53	0.76	0.76
Qual_WAVG	0.21	0.38		0.94	0.88
Quant	0.21	0.15	0.06		0.47
Quant_WAVG	0.15	0.21	0.12	0.38	

Tab. 7.2. The results of a pairwise comparison that indicate the percentage of cases (time windows) in which one group (rows) performed better than another one (columns) according to both average raw and excess returns, divided into four selected main strategies according to the LGC scheme. Source: Author's own study

A clear advantage of quantitative funds over qualitative funds can be observed only in the case of absolute return funds. Especially in this area, quantitative funds (even the ones managing smaller TNA) applying quantitative portfolio management processes managed to systematically outperform traditional portfolio managers. The opposite can be observed in the case of mixed asset funds. In the case of equity and hedge funds, only larger quant funds in terms of TNA could have managed to build their frequent advantage over the traditional portfolio managers.

Results by region

After a split of the results into four different examined strategies, it is worth verifying if they differ between four most numerous regions distinguished taking into account a primary region of investment focus. This section strictly relates to a supplementary research question of whether the differences in performance between quantitative and qualitative funds differ between the groups of funds distinguished in terms of the region of a primary investment focus.

Due to this, Figure 7.6. presents the results for four most numerous groups of funds distinguished in terms of the geographic region of a primary investment focus.

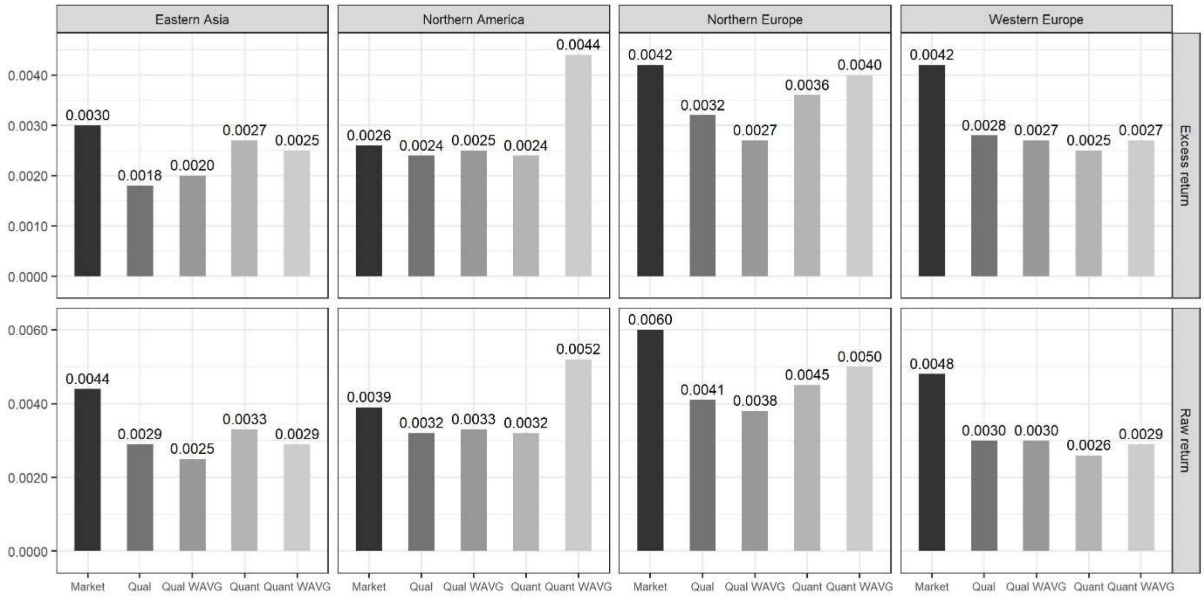

Fig. 7.6. The average monthly raw and excess returns calculated for all rolling windows of the markets (Market), qualitative funds (Qual), and quantitative funds (Quant), as well as the average monthly raw and excess returns weighted by the total net assets of qualitative (Qual WAVG) and quantitative (Quant WAVG) funds calculated for all rolling windows, in the entire research period from 01/01/2000 to 31/12/2020, divided into four selected most numerous regions of primary investment focus. Source: Author's own study

The results presented in Figure 7.6. suggest that when considering all windows tested, on average, only the TNA-weighted category of quant funds primarily investing in Northern America managed to outperform the market. Other categories in this region perform similarly to each other, but significantly worse than the TNA-weighted quant category. Quant funds also outperformed qualitative funds in the group of Eastern Asia and Northern Europe. The opposite situation took place in the group of Western Europe. To sum up, the results obtained suggest that the regions examined are substantially different in terms of the average unadjusted returns of investment funds. Moreover, as opposed to the overall results, in none of the groups except for the group of funds primarily investing in Northern America, none of the fund categories managed to outperform the market. The results obtained for the group of funds primarily investing in Northern America appear to be the most similar to the overall results compared to other groups.

It is also worth noting that, as opposed to the results split into four different strategies (Figure 7.4.), according to Figure 7.6., larger funds in terms of managed TNA do not necessarily perform better (on average) compared to smaller funds. This issue is region-dependent and refers to both quant and qual funds. Concerning quant funds, the larger ones (in terms of TNA managed) perform better in the groups of funds primarily investing in Northern America, Northern Europe, and Western Europe. In the group of funds primarily investing in Eastern Asia the opposite is true.

Figure 7.7. shows how the values of the discussed performance measures behaved across time windows and regions of a primary investment focus. The results obtained for the groups examined share many common features with the overall results. Nevertheless, as opposed to the overall results, in just a few cases, fund categories managed to systematically outperform the market starting from the window ending in 2013. This observation allows to assume that the least numerous regions, which are not included in this detailed comparison, may significantly affect the overall results.

In the group of funds primarily investing in Northern America, divergencies between the categories seem to be the least, which suggests that in this group, the returns of different categories may be the most correlated. The lowest values for almost all categories in this group can be observed in the window ending in 2008. This feature was observed also in the case of the overall results and could be related to the global financial crisis. Nevertheless, the average performance of the market decreased again in the window ending in 2011 and it is difficult to relate this phenomenon with direct aftereffects of the global financial crisis. However, these aftereffects could have a long-run dimension. In other regions, the lowest levels of performance measures discussed can be observed instead in the windows ending in years 2011-2012. The levels of performance measures in these windows are much lower compared to the levels in the window ending in 2008. Nevertheless, the same as in the case of Northern America, the aftereffects of the global financial crisis could have a long-term dimension resulting in a decreased performance also in the following years.

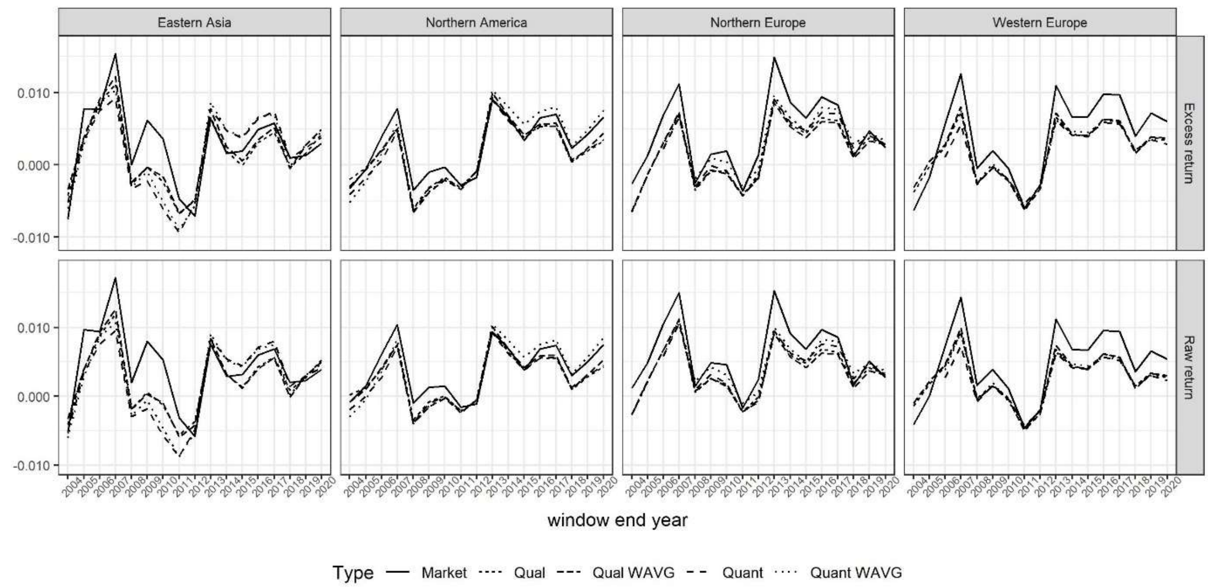

Fig. 7.7. The average monthly raw and excess returns in each time window, calculated for the markets (Market), qualitative funds (Qual), and quantitative funds (Quant), as well as the average monthly raw and excess returns in each time window weighted by the total net assets of qualitative (Qual WAVG) and quantitative (Quant WAVG) funds, divided into four most numerous regions of primary investment focus. Source: Author's own study

Table 7.3. presenting the results of a pairwise comparison and constituting a brief summary of the results presented in Figure 7.7. suggests that more often, the market outperformed almost all categories of funds in the groups of funds primarily investing in

Northern Europe, Northern America, and Western Europe. Among all groups considered, a group of funds primarily investing in Eastern Asia managed better in this matter. It especially pertains to quant funds. Considering simple average results and the TNA-weighted average results, only in the group of funds primarily investing in Northern Europe, quant funds managed more often better than qual funds. When taking into account only the TNA-weighted categories, quant funds outperformed qual funds more often in the groups of funds primarily investing in Northern America and Northern Europe. In the groups of funds primarily investing in Eastern Asia and Wester Europe qualitative funds outperformed quants more frequently. To sum up, the groups of funds distinguished in terms of the region of a primary investment focus differ in terms of the frequency of performance advantage. They also differ from the overall results.

Raw and excess returns - Eastern Asia					
	Losers				
Group	Market	Qual	Qual_WAVG	Quant	Quant_WAVG
Market		0.62	0.62	0.47	0.47
Qual	0.38		0.32	0.59	0.59
Qual_WAVG	0.38	0.62		0.62	0.59
Quant	0.53	0.41	0.32		0.38
Quant_WAVG	0.53	0.41	0.41	0.62	

Raw and excess returns - Northern America					
	Losers				
Group	Market	Qual	Qual_WAVG	Quant	Quant_WAVG
Market		0.74	0.71	0.88	0.47
Qual	0.24		0.35	0.71	0.32
Qual_WAVG	0.24	0.5		0.71	0.18
Quant	0.09	0.29	0.29		0.18
Quant_WAVG	0.53	0.59	0.76	0.71	

Raw and excess returns - Northern Europe					
	Losers				
Group	Market	Qual	Qual_WAVG	Quant	Quant_WAVG
Market		0.88	0.94	0.87	0.73
Qual	0.12		0.65	0.27	0.13
Qual_WAVG	0.06	0.29		0.2	0.13
Quant	0.13	0.6	0.73		0.03
Quant_WAVG	0.27	0.87	0.87	0.93	

Raw and excess returns - Western Europe					
	Losers				
Group	Market	Qual	Qual_WAVG	Quant	Quant_WAVG
Market		0.82	0.88	0.93	0.97
Qual	0.18		0.41	0.63	0.53
Qual_WAVG	0.12	0.53		0.6	0.6
Quant	0.07	0.1	0.4		0.2
Quant_WAVG	0.03	0.33	0.37	0.7	

Tab. 7.3. The results of a pairwise comparison that indicate the percentage of cases (time windows) in which one group (rows) performed better than another one (columns) according to both average raw and excess returns, divided into four most numerous regions of primary investment focus. Source: Author's own study

7.2. Sharpe and Treynor ratios

Overall results

The first group of the discussed relative measures of portfolio performance consists of the Sharpe ratio and Treynor ratio, i.e., measures directly related to the CAPM model. They were discussed in Section 4.1.3. and described with Formulas 4.15. and 4.17., respectively. The same as in the case of the raw and excess returns, the results for the overall sample will be discussed first.

Referring to Figure 7.8., the average results of all fund categories are higher than the results of the market. Quant funds seem to perform better compared to other categories, especially the ones managing larger TNA, as the TNA-weighted average results for the quants gained a significant advantage over the other categories compared. These results are in line with the ones obtained in the studies by Chuang and Kuan (2018), as well as Parvez and Sudhir (2005), who proposed that generally quantitative funds outperformed qualitative funds in terms of the Sharpe ratio. However, it should be taken into account that they considered only hedge funds and equity funds, respectively i.e., groups that constitute just a part of the sample of this study.

Despite the fact that the measures discussed apply different risk proxies, both of them allow for drawing similar conclusions. It is in line with the explanations proposed by Zamojska (2012), pertaining to the similarity of rankings obtained with the use of the CAPM-based portfolio performance measures. It is interesting whether the results calculated with the use of other relative measures of portfolio performance allow for drawing similar conclusions. Going back to the results presented in Figure 7.8., the major difference between the results obtained for the Sharpe ratio and Treynor ratio pertains to qualitative funds. According to the Treynor ratio, qualitative funds managing larger TNA performed slightly worse compared to smaller qualitative funds.

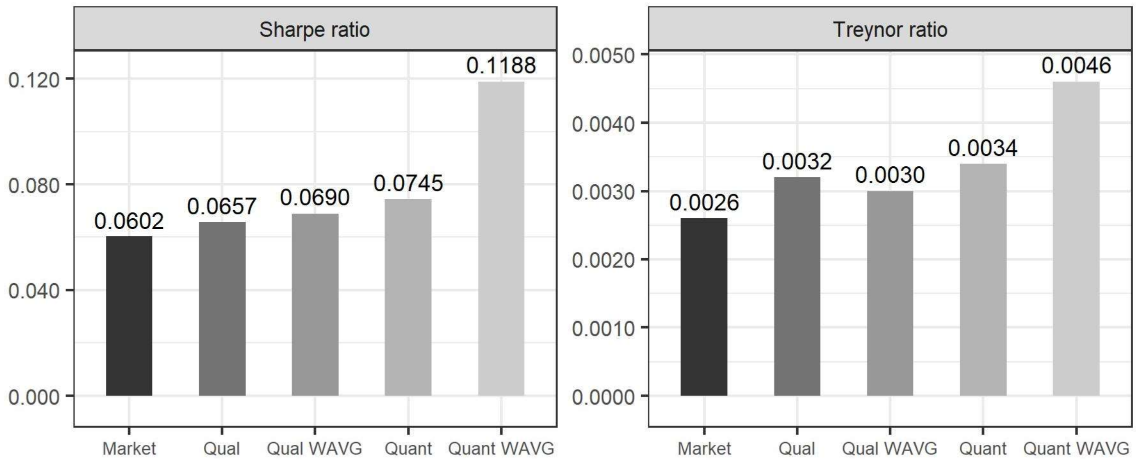

Fig. 7.8. The average Sharpe and Treynor ratios calculated for monthly returns in all rolling windows of the markets (Market), qualitative funds (Qual), and quantitative funds (Quant), as well as the average Sharpe and Treynor ratios calculated for monthly returns in all rolling windows weighted by the total net assets of qualitative (Qual WAVG) and quantitative (Quant WAVG) funds, in the entire research period from 01/01/2000 to 31/12/2020. Source: Author's own study

Comparing the results of the Sharpe ratio and Treynor ratio with the results of raw and excess returns, there are some differences between these two groups of measures. The biggest difference refers to the market outperforming most of fund categories according to raw and excess returns. In the case of the CAPM-based measures it was not observable. Moreover, the Sharpe ratio indicates a slight difference between quantitative and qualitative funds at the level of non-weighted categories in favour of quantitative funds. In the case of raw and excess return no visible differences at the level of non-weighted categories could be observed. Of course, there is also a similarity between the aforementioned groups of performance measures like the one referring to the outperformance of the quants managing smaller TNA by the larger quants. Again, it may be related to the application of more advanced quantitative portfolio management processes by larger quants, which in turn generates higher performance.

Similarly as in the case of the unadjusted portfolio performance measures, following Harvey et al. (2017), the 25th and 75th percentiles of the average monthly Sharpe and Treynor ratios, as well as spreads between these percentiles, have been calculated for all rolling windows of qualitative (Qual) and quantitative (Quant) funds in the entire research period from 01/01/2000 to 31/12/2020. The results are presented in Figure 7.9. According to the results for the Treynor ratio, the differences between the percentiles and spreads of quant and qual funds are very low, which suggests that both fund types are similarly homogenous in terms of Treynor ratio. The situation looks a little different in the case of the Sharpe ratio, as the difference between the spreads of quant and qual funds is more significant. This is mostly due to the difference between the 75th percentiles. In the case of quant funds, the upper 25% of Sharpe ratio observations have higher values.

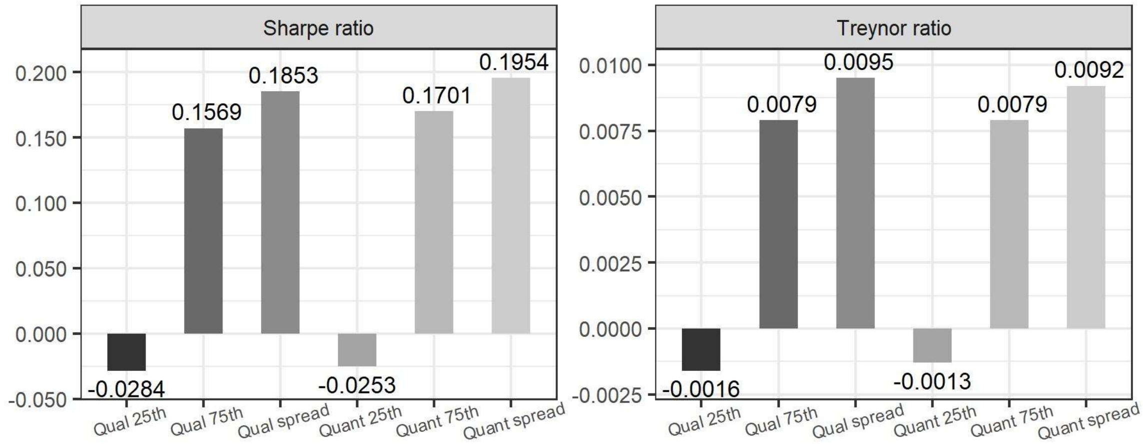

Fig. 7.9. The 25th and 75th percentile of the average monthly Sharpe and Treynor ratios, as well as spread between these percentiles, calculated for all rolling windows of qualitative (Qual) and quantitative (Quant) funds in the entire research period from 01/01/2000 to 31/12/2020. Source: Author’s own study

According to Figure 7.10., similarly to the case of the overall results obtained for raw and excess returns, the market systematically outperformed all fund categories by the window ending in 2010-2011. In the following windows, the opposite was true and the market was systematically outperformed by the fund categories. Especially quant funds managing larger TNA tended to do great in this matter. It should be noted that in these windows the advantage of all fund categories over the market was significantly higher compared to the results received for the unadjusted returns. It suggests that funds are less risky. Simple averages of results obtained for the Sharpe ratio and the Treynor ratio for different fund categories behave similarly over the windows, suggesting their positive correlation. Similarly as in the case of the raw and excess returns, all fund categories dropped in the window ending in 2008 reaching the lowest values of all windows, which may be related to the global financial crisis.

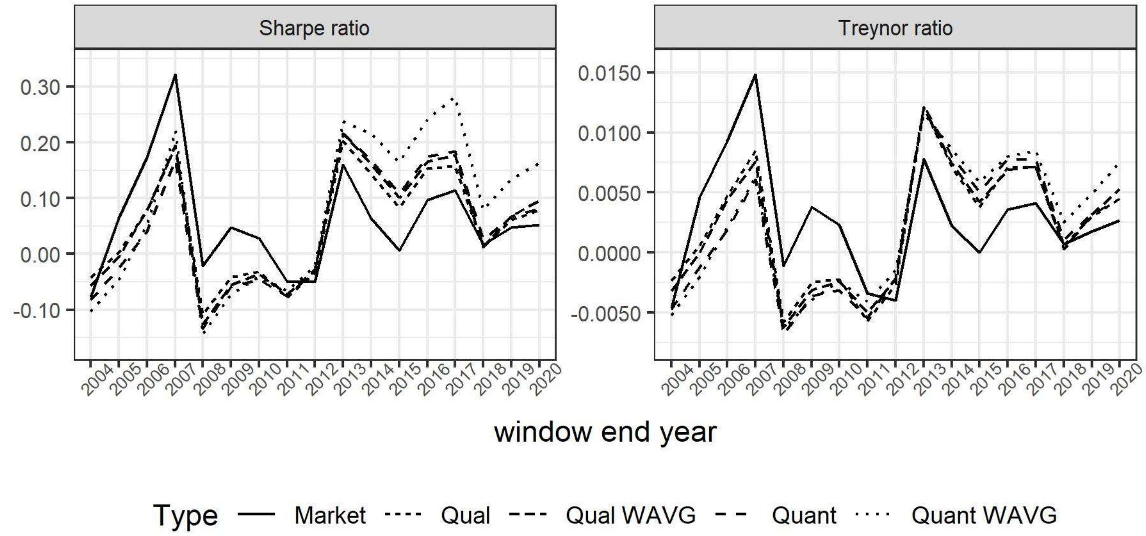

Fig. 7.10. The average Sharpe and Treynor ratios calculated for monthly returns in each time window of the markets (Market), qualitative funds (Qual) and quantitative funds (Quant), as well as the average Sharpe and Treynor ratios calculated for monthly returns in each time window weighted by total net assets of qualitative (Qual WAVG) and quantitative (Quant WAVG) funds. Source: Author's own study

According to Table 7.4. that summarises the results presented in Figure 7.10., all fund categories just a little more frequently outperformed the market. Also, quant funds outperformed qualitative funds just a little more often. These are the biggest differences between the results of the CAPM-based measures and the raw and excess returns obtained for the overall sample. It should be noted that Table 7.4. summarized the results presented in Figure 7.10. that pertained to the entire research period. From about half of the research period (see Figure 7.10.) there were some crucial changes (e.g., market stopped outperforming funds, quants managing larger TNA started to outperformed other categories) that are not clearly indicated in Table 7.4.

Sharpe and Treynor ratios - Overall results					
	Losers				
Group	Market	Qual	Qual_WAVG	Quant	Quant_WAVG
Market		0.47	0.47	0.47	0.47
Qual	0.53		0.47	0.41	0.41
Qual_WAVG	0.53	0.5		0.56	0.38
Quant	0.53	0.56	0.41		0.24
Quant_WAVG	0.53	0.59	0.59	0.76	

Tab. 7.4. The results of a pairwise comparison that indicate the percentage of cases (time windows) in which one group (rows) performed better than another one (columns) according to both the Sharpe ratio and the Treynor ratio. Source: Author's own study

Results by strategy

Referring to a supplementary research question pertaining to differences between strategies in terms of differences between the performance of quantitative and qualitative funds, Figure 7.11. presents the results broken down to selected four main strategies according to the Lipper Global Classification scheme. Similarly as in the case of the unadjusted returns, the average performance differs significantly between strategies. However, the results received for the relative measures of portfolio performance allowed to draw different conclusions compared to the results received for the unadjusted returns. Accounting for risk (responsible for the aforementioned differences) especially affected the relation between the average values of the performance measures of the market and all fund categories. Namely, after accounting for risk, the performance of the market decreased in comparison to the performance of fund categories in all strategies. It suggests that on average funds applied less risky strategies compared to a passive investment in the equity market benchmark.

Quantitative funds clearly seem to manage better than the market and qualitative funds in the groups of absolute return and equity funds. Larger quant funds in terms of TNA managed seem to perform even better. Accounting for risk revealed a very interesting phenomenon, namely, according to the Sharpe ratio, the performance of quant absolute return funds has significantly diminished the advantage of quant equity funds over them. Moreover, quant absolute return funds outperformed more risky qualitative equity funds and all fund categories in the group of mixed asset funds. This is mostly due to a low volatility of the returns of quant absolute return funds. Traditional absolute return managers did not manage to achieve this.

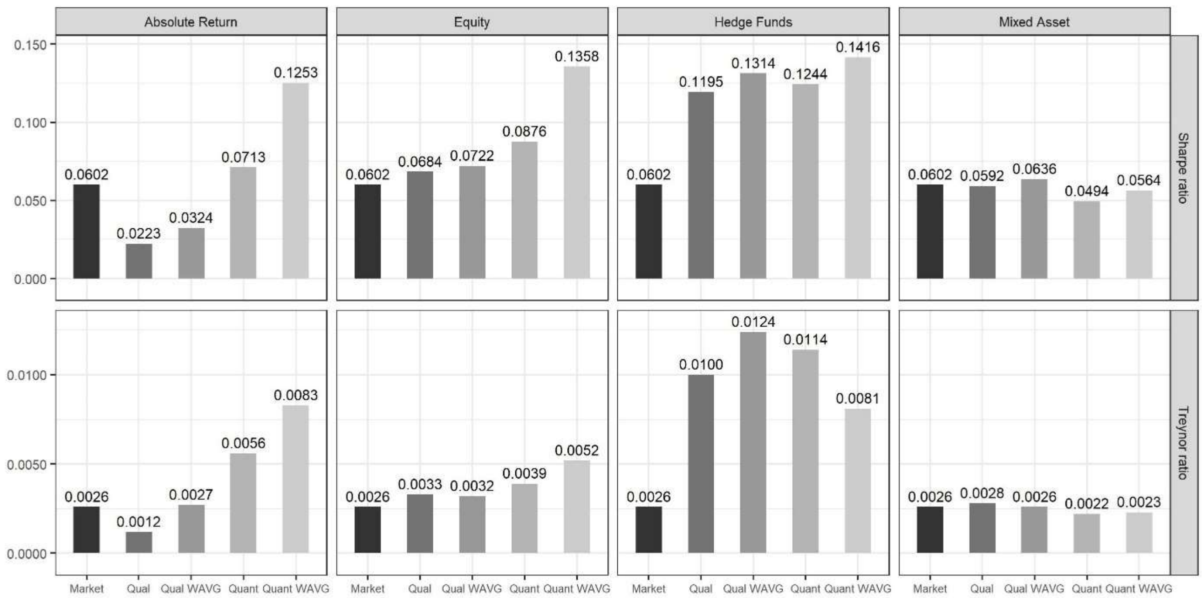

Fig. 7.11. The average Sharpe and Treynor ratios calculated for monthly returns in all rolling windows of the markets (Market), qualitative funds (Qual), and quantitative funds (Quant), as well as the average Sharpe and Treynor ratios calculated for monthly returns in all rolling windows weighted by the total net assets of qualitative (Qual WAVG) and quantitative (Quant WAVG) funds, in the entire research period from 01/01/2000 to 31/12/2020, divided into selected four main strategies according to the LGC scheme. Source: Author's own study

In terms of the Treynor ratio, quant absolute return funds have even outperformed all categories from the groups of equity and mixed asset funds. This is due to a low exposure of quant absolute return funds to a systematic risk, which could not be achieved by qualitative absolute return funds. It suggests that the application of the quantitative portfolio management processes especially in absolute return funds may deliver much better results compared to traditional approaches to portfolio management.

Quantitative portfolio management processes also seem to bring a clear advantage over traditional approaches to portfolio management in the group of equity funds. Nevertheless, the advantage of quant funds in this group is lower than in the group of absolute return funds. Equity funds seem to have a high exposure to a systematic risk and thus their performance according to Treynor ratio is lower compared to quant absolute return funds.

In the group of hedge funds, the quants on average (non-weighted) seem to outperform qualitative funds. However, according to the Treynor ratio, the TNA-weighted category of quant funds is marked by the lowest average performance among all fund categories, which suggests that larger quant hedge funds may have higher systematic risk compared to smaller quant hedge funds. Despite the riskiest strategies applied, hedge funds generate the highest performance across all strategies. In the group of mixed asset funds, quant funds are slightly outperformed by qualitative funds and the market. It is the only group of funds in which the quantitative portfolio management process does not have any beneficial impact on performance.

Figure 7.12. shows the behaviour of the Sharpe ratio and Treynor ratio over the time windows for different strategies. It reveals some differences compared to the results for raw and excess returns. For instance, absolute return funds became one of the most volatile groups from the least volatile ones in the case of the unadjusted returns. On the other hand, equity and mixed asset funds became the least volatile from the most volatile ones in the case of the unadjusted returns. It may suggest that the risk exposure of absolute return funds varied much more over time windows compared to the risk exposure of other groups. Also, differences between the categories in the case of equity and mixed asset funds are the lowest, suggesting that they may be the most correlated. Again, in the case of all strategies, a diminished performance in the windows ending in 2008-2012 can be observed.

There are also some differences between the Sharpe ratio and the Treynor ratio, especially referring to equity and mixed asset funds. Namely, taking into account the Treynor ratio, as well as equity and mixed asset funds, the values of this measure are the least volatile over the windows compared to other strategies. This could not be observed in the case of the Sharpe ratio. Most likely, it results from a high systematic risk exposure of equity and mixed asset funds in comparison to other strategies.

Similarly as in the case of the overall results, starting from a certain window, the market began to be outperformed by most fund categories in all groups distinguished in terms of strategy. In the case of absolute return, equity, and mixed asset funds, it was the window ending in 2011-2012. In the case of hedge funds, it could be even window ending in 2008.

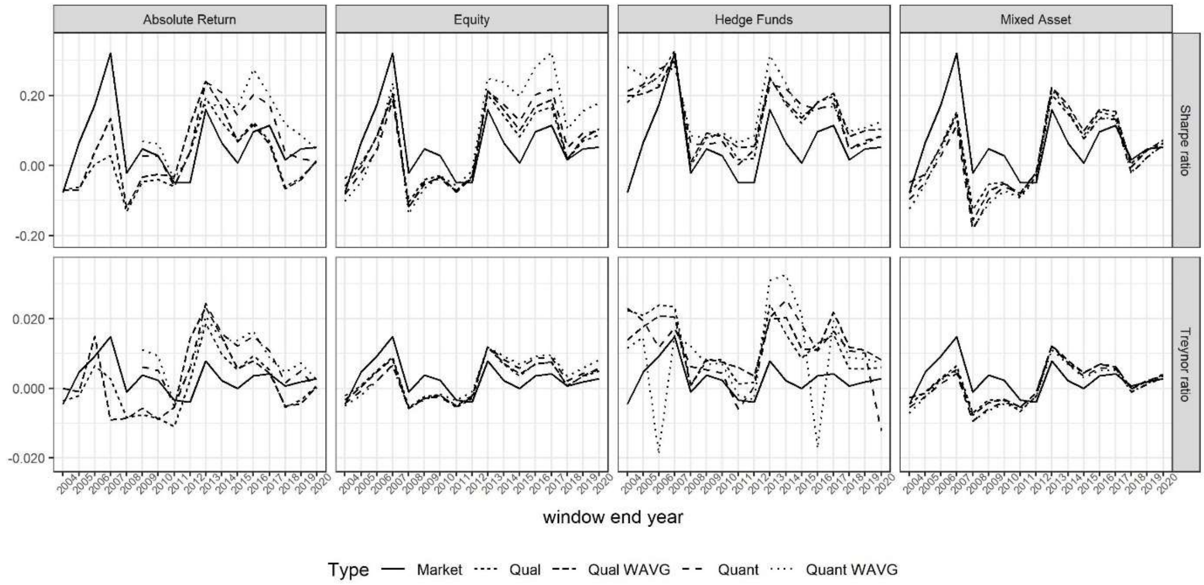

Fig. 7.12. The average Sharpe and Treynor ratios calculated for monthly returns in each time window, calculated for the markets (Market), qualitative funds (Qual) and quantitative funds (Quant), as well as the average Sharpe and Treynor ratios calculated for monthly returns in each time window weighted by the total net assets of qualitative (Qual WAVG) and quantitative (Quant WAVG) funds, divided into selected four main strategies according to the LGC scheme. Source: Author's own study

Referring to Table 7.5., which constitutes a brief summary of the results presented in Figure 7.12., similarly as in the case of raw and excess returns, there are some significant differences between the strategies in terms of the frequency of the performance advantages of categories. However, as opposed to the raw and excess returns, in the case of the CAPM-based performance measures, funds started to outperform the market more often. A clearly systematic outperformance of the market by funds can be observed in the group of hedge funds and in the group of absolute return funds. However, in the group of absolute return funds, it applied only to quant funds.

What is more, similarly as in the case of the raw and excess returns, quant absolute return funds had a clear and systematic advantage over qualitative funds. Similarly as in the case of the unadjusted returns, quant funds managing larger TNA outperformed other categories more frequently (except for the case of mixed asset funds). However, when simple average results were taken into account, in the groups of equity and hedge funds, the differences between quant and qual funds were slight.

Sharpe and Treynor ratios - Absolute Return					
	Losers				
Group	Market	Qual	Qual_WAVG	Quant	Quant_WAVG
Market		0.62	0.56	0.29	0.12
Qual	0.38		0.41	0.04	0.08
Qual_WAVG	0.44	0.59		0.25	0.29
Quant	0.71	0.92	0.75		0.29
Quant_WAVG	0.88	0.92	0.71	0.71	

Sharpe and Treynor ratios - Equity					
	Losers				
Group	Market	Qual	Qual_WAVG	Quant	Quant_WAVG
Market		0.41	0.44	0.44	0.47
Qual	0.59		0.44	0.44	0.38
Qual_WAVG	0.56	0.56		0.5	0.32
Quant	0.56	0.56	0.44		0.26
Quant_WAVG	0.53	0.62	0.68	0.71	

Sharpe and Treynor ratios - Hedge Funds					
	Losers				
Group	Market	Qual	Qual_WAVG	Quant	Quant_WAVG
Market		0	0.03	0.09	0.09
Qual	1		0.38	0.53	0.38
Qual_WAVG	0.97	0.62		0.65	0.5
Quant	0.91	0.47	0.35		0.35
Quant_WAVG	0.91	0.62	0.5	0.65	

Sharpe and Treynor ratios - Mixed Asset					
	Losers				
Group	Market	Qual	Qual_WAVG	Quant	Quant_WAVG
Market		0.53	0.5	0.59	0.59
Qual	0.47		0.47	0.79	0.85
Qual_WAVG	0.5	0.5		0.85	0.97
Quant	0.41	0.18	0.09		0.53
Quant_WAVG	0.41	0.15	0.03	0.44	

Tab. 7.5. The results of a pairwise comparison that indicate the percentage of cases (time windows) in which one group (rows) performed better than another one (columns) according to both the Sharpe ratio and the Treynor ratio, divided into selected four main strategies according to the LGC scheme. Source: Author's own study

Similarly as in the case of the raw and excess returns, quantitative mixed asset funds were dominated by qualitative mixed asset funds, which confirms that the implementation of the quantitative portfolio management process does not have any beneficial impact on the performance of this type of funds.

Taking into account absolute return and equity funds, similarly as in the case of the overall sample, the larger TNA had a more positive impact on performance in the group of quantitative funds compared to qualitative funds. When it comes to hedge and mixed asset funds, this impact was similar in both groups.

Results by region

Referring to a supplementary research question pertaining to differences between regions in terms of differences between the performance of quantitative and qualitative funds, Figure 7.13. presents the average results for four most numerous groups of funds distinguished in terms of the region of a primary investment focus. The results received confirm the conclusions drawn from the analysis of results for the raw and excess returns stating that performance differs significantly between regions (see Figure 7.6.). The results provided for the unadjusted returns and the relative measures of portfolio performance discussed here share some other similarities. However, there are also some differences between them. The major difference is that after accounting for risk, it is much easier for fund categories to outperform the market. The same difference was emphasized in the discussion of the overall results and results for strategies.

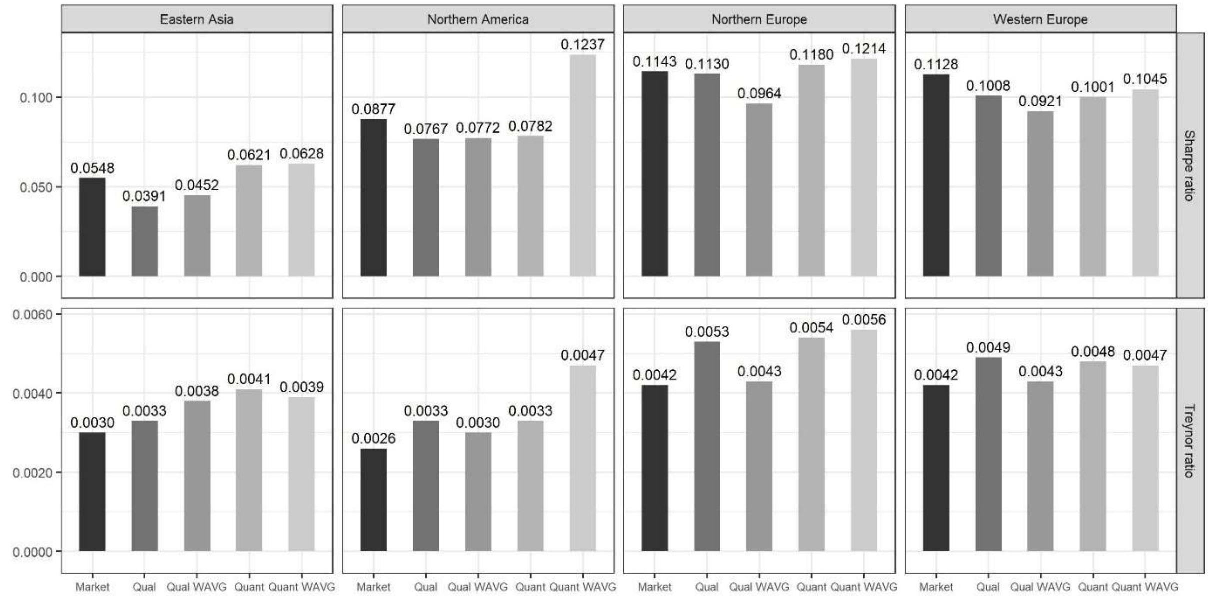

Fig. 7.13. The average Sharpe and Treynor ratios calculated for monthly returns in all rolling windows of the markets (Market), qualitative funds (Qual) and quantitative funds (Quant), as well as the average Sharpe and Treynor ratios calculated for monthly returns in all rolling windows weighted by the total net assets of qualitative (Qual WAVG) and quantitative (Quant WAVG) funds, in the entire research period from 01/01/2000 to 31/12/2020, divided into four most numerous regions of primary investment focus. Source: Author's own study

Similarly as in the case of raw and excess returns, quant funds outperformed qualitative funds in the group of funds primarily investing in the region of Eastern Asia and just slightly in Northern Europe. In the case of Northern America, when considering non-weighted results, the average performance of quantitative and qualitative funds was very similar. However, when considering TNA-weighted categories, quantitative funds appeared to have a clear advantage over qualitative funds. It may suggest that especially larger quantitative funds were able to generate higher performance. In the group of funds primarily investing in Western Europe, quantitative and qualitative funds did not seem to differ much in terms of the non-weighted results. However, when considering the TNA-weighted results, qualitative funds with larger TNA appeared to perform slightly worse compared to smaller qualitative funds. It could not be observable in the case of raw and excess returns. Only in the case of Northern America, quant funds managing larger TNA appeared to perform significantly better than the smaller quants. In other regions, there were no clear differences in the average performance between larger and smaller quant funds. Clear differences between larger and smaller funds could be observed in the groups of qualitative funds primarily investing in Eastern Asia, Northern Europe and Western Europe.

Figure 7.14. presents the behaviour of the CAPM-based relative measures of portfolio performance over time windows. The results presented in the this figure share many similarities with the results for raw and excess returns (see Figure 7.7.), like the similarity of trends in the examined categories and a common decrease of results in the windows ending in 2008-2012. When considering the Treynor ratio and the results obtained for the groups of funds primarily investing in Eastern Asia and Northern America, fund categories appear to outperform the market (with few exceptions) starting from the windows ending in 2011. A similar situation

could be observed in the case of the overall results (see Figure 7.10.). In the previous windows, the market systematically outperformed the fund categories. A similar phenomenon can be observed also in the case of other two regions; however, it is not as clear as in the case of the groups of Eastern Asia and Northern America. When it comes to the Sharpe ratio, the outperformance of funds by the market by the windows ending around 2011 was rather clear in all groups distinguished in terms of the region of a primary investment focus. However, the outperformance of the market by funds in the following windows could not be observed as often as in the case of the overall results.

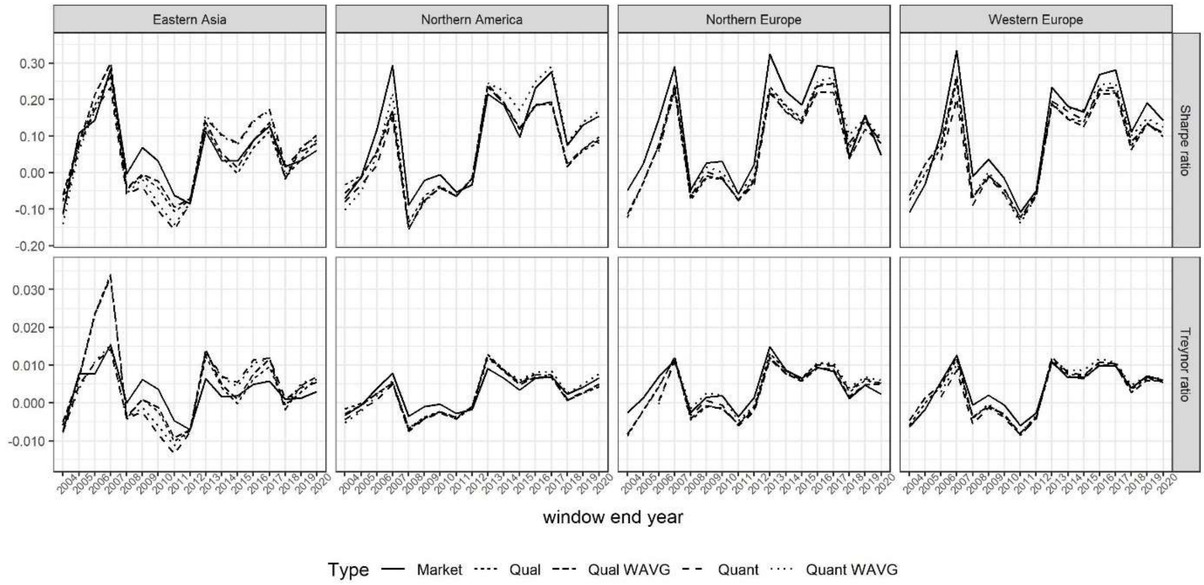

Fig. 7.14. The average Sharpe and Treynor ratios calculated for monthly returns in each time window, calculated for the markets (Market), qualitative funds (Qual), and quantitative funds (Quant), as well as the average Sharpe and Treynor ratios calculated for monthly returns in each time window weighted by the total net assets of qualitative (Qual WAVG) and quantitative (Quant WAVG) funds, divided into four most numerous regions of primary investment focus. Source: Author's own study

Referring to Table 7.6., which can be treated as a brief summary of the results presented in Figure 7.14., the conclusion that can be drawn from the results for the relative measures of portfolio performance are similar to the ones made on the basis of the results obtained for raw and excess returns (see Table 7.3.). Similarly as in the case of the raw and excess returns, taking into account simple average categories, quant funds rarely outperformed qualitative funds in the groups of funds primarily investing in Eastern Asia, Northern America, and Western Europe. After accounting for TNA, quantitative funds turned out to outperform qualitative funds more frequently in the groups of funds primarily investing in Northern America, Northern Europe, and Western Europe. The main difference between the results for the CAPM-based measures and risk-unadjusted returns was that most funds categories in all groups except for Eastern Asia increased their rate of windows in which they outperformed the market.

Sharpe and Treynor ratios - Eastern Asia					
	Losers				
Group	Market	Qual	Qual_WAVG	Quant	Quant_WAVG
Market		0.53	0.47	0.44	0.5
Qual	0.47		0.09	0.56	0.53
Qual_WAVG	0.53	0.88		0.68	0.62
Quant	0.53	0.41	0.32		0.47
Quant_WAVG	0.5	0.47	0.38	0.5	

Sharpe and Treynor ratios - Northern America					
	Losers				
Group	Market	Qual	Qual_WAVG	Quant	Quant_WAVG
Market		0.59	0.65	0.71	0.47
Qual	0.41		0.56	0.71	0.41
Qual_WAVG	0.32	0.38		0.65	0.32
Quant	0.29	0.29	0.35		0.18
Quant_WAVG	0.53	0.56	0.65	0.76	

Sharpe and Treynor ratios - Northern Europe					
	Losers				
Group	Market	Qual	Qual_WAVG	Quant	Quant_WAVG
Market		0.74	0.82	0.77	0.6
Qual	0.26		0.65	0.6	0.27
Qual_WAVG	0.18	0.32		0.37	0.17
Quant	0.23	0.37	0.63		0.13
Quant_WAVG	0.4	0.7	0.83	0.87	

Sharpe and Treynor ratios - Western Europe					
	Losers				
Group	Market	Qual	Qual_WAVG	Quant	Quant_WAVG
Market		0.74	0.79	0.8	0.73
Qual	0.26		0.47	0.57	0.27
Qual_WAVG	0.21	0.53		0.53	0.3
Quant	0.2	0.43	0.47		0.13
Quant_WAVG	0.27	0.73	0.7	0.83	

Tab. 7.6. The results of a pairwise comparison that indicate the percentage of cases (time windows) in which one group (rows) performed better than another one (columns) according to both the Sharpe ratio and the Treynor ratio, divided into four most numerous regions of primary investment focus. Source: Author's own study

7.3. Measures based on Value at Risk (VaR)

Overall results

The next group of the relative measures of portfolio performance that will be discussed consists of measures based on the concept of value at risk and comprises two ratios namely, excess return on VaR and excess return on CVaR. They were discussed in Section 4.1.3. and described with Formulas 4.28. and 4.29., respectively. Measures considered in this section are expressed in percentage terms. All results presented in this section were initially negative (due to a negative denominator); however, eventually they are presented as absolute values in order to make their interpretation easier. Higher values of VaR-based measures will indicate higher performance. Similarly as in the case of previous performance measures, the discussion of results will focus first on the results for the overall sample.

The average results for the overall sample taking into account all windows tested in the entire research period from 01/01/2000 to 31/12/2020 are presented in Figure 7.15. Quantitative funds appear to slightly outperform qualitative funds and the market. When considering TNA-weighted categories, the difference between quantitative funds and qualitative funds is even higher. Similarly as in the case of the CAPM-based measures, all fund categories slightly outperformed the market. What is worth adding, similarly as in the case of all previously discussed measures, larger TNA under management had a clear connection with higher performance only in the case of quantitative funds. In the case of qualitative funds, this connection was slight. The similarity of conclusions that can be drawn from the VaR-based and CAPM-based measures suggests that portfolio management skills related to return variability and systematic risk management on average go hand in hand with tail risk management.

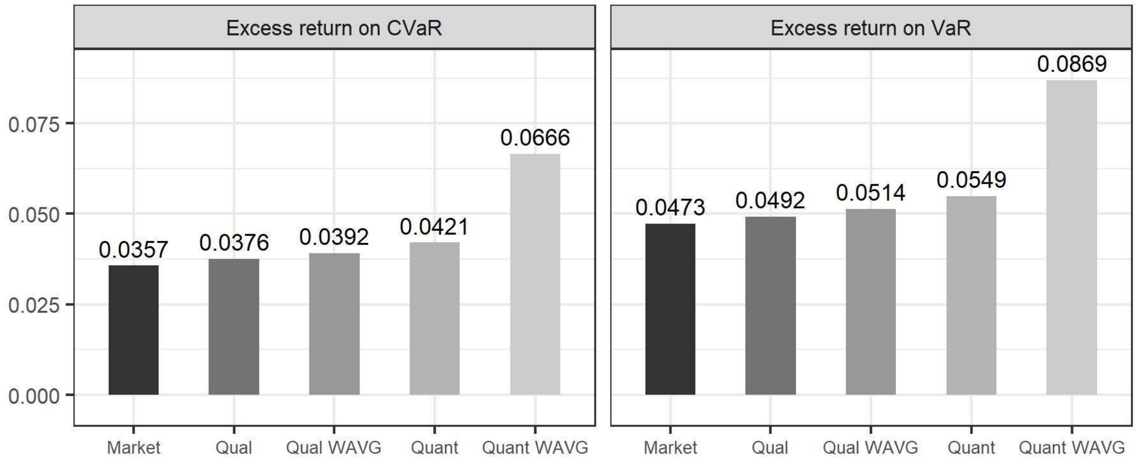

Fig. 7.15. The average excess return on VaR and the average excess return on CVaR calculated for monthly returns in all rolling windows of the markets (Market), qualitative funds (Qual), and quantitative funds (Quant), as well as the average excess return on VaR and the average excess return on CVaR calculated for monthly returns in all rolling windows weighted by the total net assets of qualitative (Qual WAVG) and quantitative (Quant WAVG) funds, in the entire research period from 01/01/2000 to 31/12/2020. Source: Author's own study

The construction of VaR-based portfolio performance measures is different compared to the construction of classic CAPM-based measures like the Sharpe ratio or Treynor ratio. Nevertheless, they allow for drawing similar conclusions, at least so far. This is in line with the findings of Eling and Schuhmacher (2007), Eling (2008), Ornelas, Silva, and Fernandes (2012), as well as Zakamouline (2010), pertaining to the similarities of fund performance rankings developed with the use of different portfolio performance measures.

Moving to the homogeneity of quantitative and qualitative funds in terms of the distributions of their VaR-based portfolio performance measures, Figure 7.16. suggests that there are some slight differences between spreads of quantitative and qualitative funds. The differences result from the higher 75th percentiles of quant funds suggesting that the upper 25% of observations of both VaR-based measures in the quant group have higher values. Similar results were obtained for the Sharpe ratio.

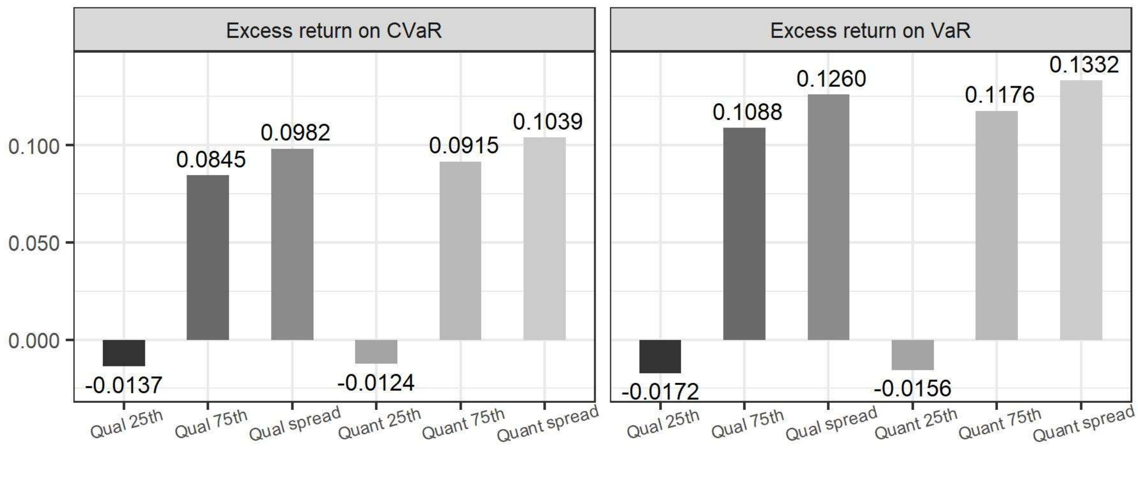

Fig. 7.16. The 25th and 75th percentile of the average monthly excess return on VaR and excess return on CVaR, as well as spread between these percentiles, calculated for all rolling windows of qualitative (Qual) and quantitative (Quant) funds in the entire research period from 01/01/2000 to 31/12/2020. Source: Author's own study

Figure 7.17. presents the average VaR-based performance measures, as well as the average VaR-based performance measures weighted by TNA, calculated separately for each time window. Again, similarly as in the case of previously discussed performance measures, Figure 7.17. indicates that the market systematically outperformed all fund categories by the window ending in 2011-2012. In the following windows, the market tended to be outperformed by the other categories, especially by the quant funds managing larger TNA. The category of the TNA-weighted quant funds developed its systematic advantage over the other fund categories as well. Furthermore, the values of the VaR-based performance measures of fund categories appear to be positively correlated due to their similar behaviour. Eventually, similarly as in the case of previous measures discussed, all fund categories dropped in the window ending in 2008 reaching the lowest values of all windows, which may be related to the global financial crisis.

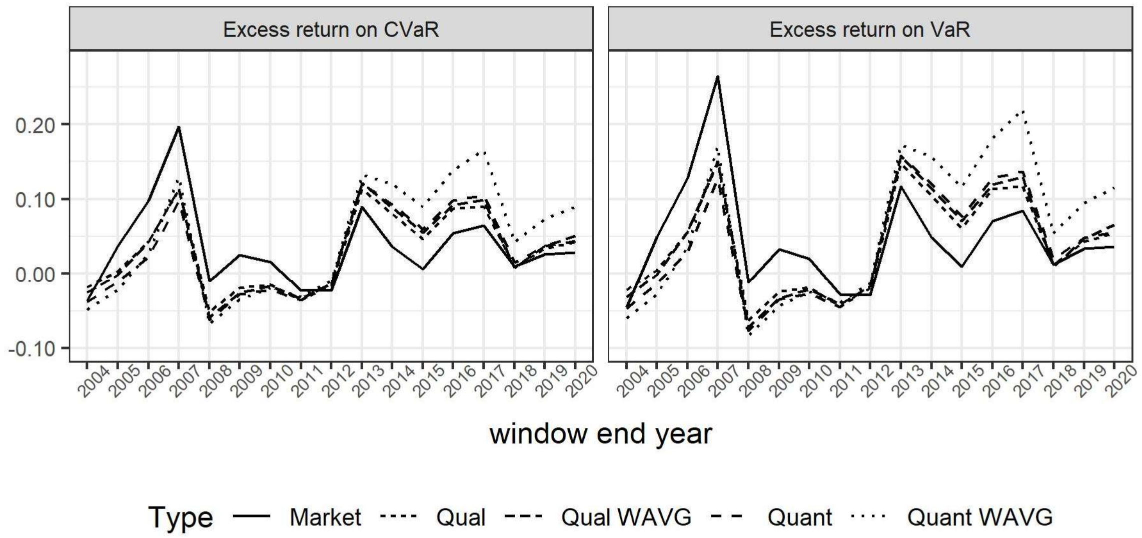

Fig. 7.17. The average excess return on VaR and the average excess return on CVaR calculated for monthly returns in each time window of the markets (Market), qualitative funds (Qual) and quantitative funds (Quant), as well as the average excess return on VaR and the average excess return on CVaR calculated for monthly returns in each time window weighted by the total net assets of qualitative (Qual WAVG) and quantitative (Quant WAVG) funds. Source: Author's own study

Table 7.7. makes an attempt to briefly summarise the results presented in Figure 7.17. According to Table 7.7., the percentage of cases where quantitative and qualitative funds outperformed each other was similar. Nevertheless, when comparing the TNA-weighted categories, quant funds outperformed qualitative funds more often. All fund categories outperformed the market in a little more than 50% of the cases. Similarly as in the case of previously discussed measures, portfolio management processes applied by larger funds (in terms of TNA managed) contributed to a more frequent outperformance of smaller funds by larger funds in the group of quant funds compared to the group of qualitative funds. The results presented in Table 7.7. allow for drawing very similar conclusions to those, which were drawn on the basis of the results for the classic CAPM-based performance ratios.

Measures based on value at risk (VaR) - Overall results					
	Losers				
Group	Market	Qual	Qual_WAVG	Quant	Quant_WAVG
Market		0.47	0.47	0.47	0.47
Qual	0.53		0.41	0.47	0.35
Qual_WAVG	0.53	0.59		0.53	0.35
Quant	0.53	0.53	0.44		0.24
Quant_WAVG	0.53	0.65	0.65	0.76	

Tab. 7.7. The results of a pairwise comparison that indicate he percentage of cases (time windows) in which one group (rows) performed better than another one (columns) according to both the average excess return on VaR and the average excess return on CVaR. Source: Author's own study

Results by strategy

In order to answer a supplementary research question of whether differences in performance between quantitative and qualitative funds differ between the groups of funds distinguished in terms of strategy, the calculations of the VaR-based performance measures were also obtained for individual strategies. The results obtained for the VaR-based performance measures calculated for the overall sample and presented so far allowed for drawing similar conclusions to conclusions drawn from the results of the classic CAPM-based portfolio performance measures. It will be interesting to see if there are also many similarities between the results for VaR-based and CAPM-based performance measures at the level of individual strategies.

Figure 7.18. breaks down the average results of the VaR-based performance measures calculated for all windows in the entire research period from 01/01/2000 to 31/12/2020 to four main strategies according to the Lipper Global Classification scheme. Quantitative funds on average outperformed qualitative funds in the case of groups of absolute return, equity, and hedge funds. The opposite was true in the case of mixed asset funds. Only in the group of mixed asset funds, the average performance of quant funds was even lower than the average performance of the market. In the case of both qualitative and quantitative funds, funds managing larger TNA managed better. It was especially clear in the case of the quant absolute return and equity funds.

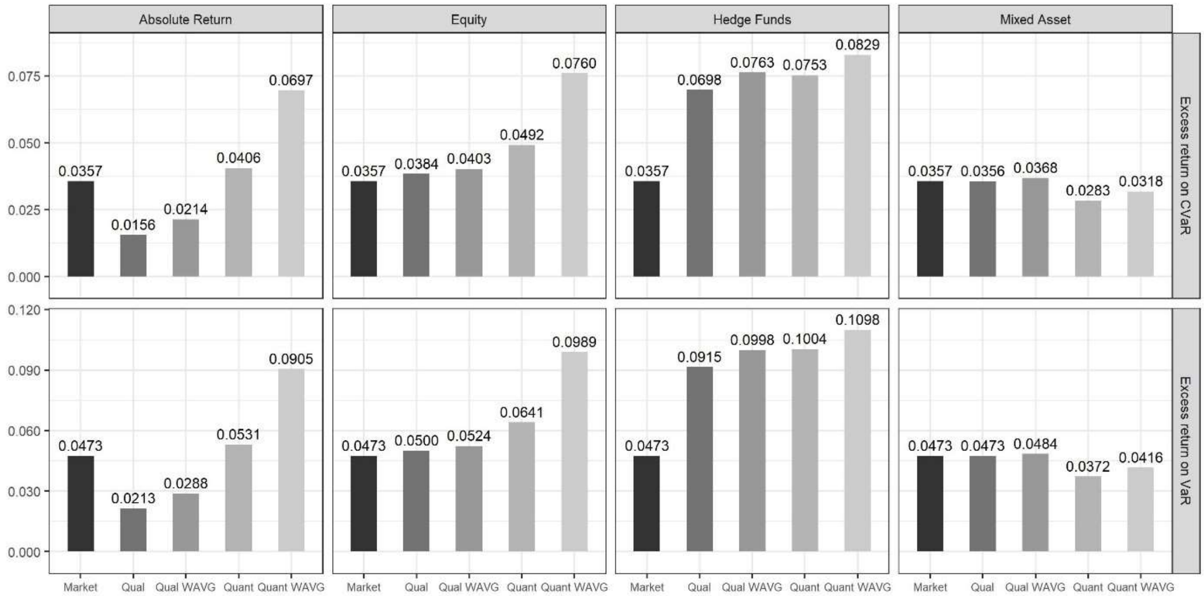

Fig. 7.18. The average excess return on VaR and the average excess return on CVaR calculated for monthly returns in all rolling windows of the markets (Market), qualitative funds (Qual), and quantitative funds (Quant), as well as the average excess return on VaR and the average excess return on CVaR calculated for monthly returns in all rolling windows weighted by the total net assets of qualitative (Qual WAVG) and quantitative (Quant WAVG) funds, in the entire research period from 01/01/2000 to 31/12/2020, divided into selected four main strategies according to the LGC scheme. Source: Author's own study

The results presented in Figure 7.18. allow for making similar conclusions to those drawn on the basis of the results received for the classic CAPM-based performance measures (especially the Sharpe ratio). However, there are also some differences between the results obtained for these two groups of the relative measures of performance. One of the major differences between the results received for the CAPM-based and VaR-based performance measures refers to the results for the Treynor ratio of equity and mixed asset funds. The Treynor ratio, especially in these two groups, had low values and affected the results of the comparative analysis between strategies. According to the Treynor ratio, quant absolute return funds outperformed on average all equity and mixed asset fund categories. It is understandable, as it is easy to imagine that the aforementioned strategies are exposed to systematic risk the most. Taking this into account, it seems that it is even more correct to state that the results of the VaR-based performance measures allow for drawing more similar conclusions to those made on the basis of the results for the Sharpe ratio. It also suggests that portfolio management skills related to managing the variability of returns on average go hand in hand with tail risk management. On the other hand, tail risk management does not seem to go along as much with systematic risk management.

Another major difference between the results for CAPM-based and VaR-based performance measures also refers to the results for the Treynor ratio but this time it pertains directly to the TNA-weighted results of quantitative funds. According to the Treynor ratio, larger quant funds were highly exposed to a systematic risk, which significantly decreased their relative performance. This phenomenon can be observed in the groups of absolute return, equity, and hedge funds. Thus, again it seems that it is even more correct to state that the results of VaR-based performance measures are more similar to the results obtained for the Sharpe ratio.

Figure 7.19. presents the behaviour of the results of VaR-based performance measures over the windows for individual strategies and categories. The results obtained for the two VaR-based measures allow to draw very consistent conclusions. Such a high level of consistency could not be observed in the case of CAPM-based measures. The behaviour of the results of both VaR-based performance measures reminds the behaviour of the results of the Sharpe ratio the most, allowing to draw similar conclusions. They are less similar to the results of the Treynor ratio, as a high systematic risk significantly affected the relative performance of equity and mixed funds especially.

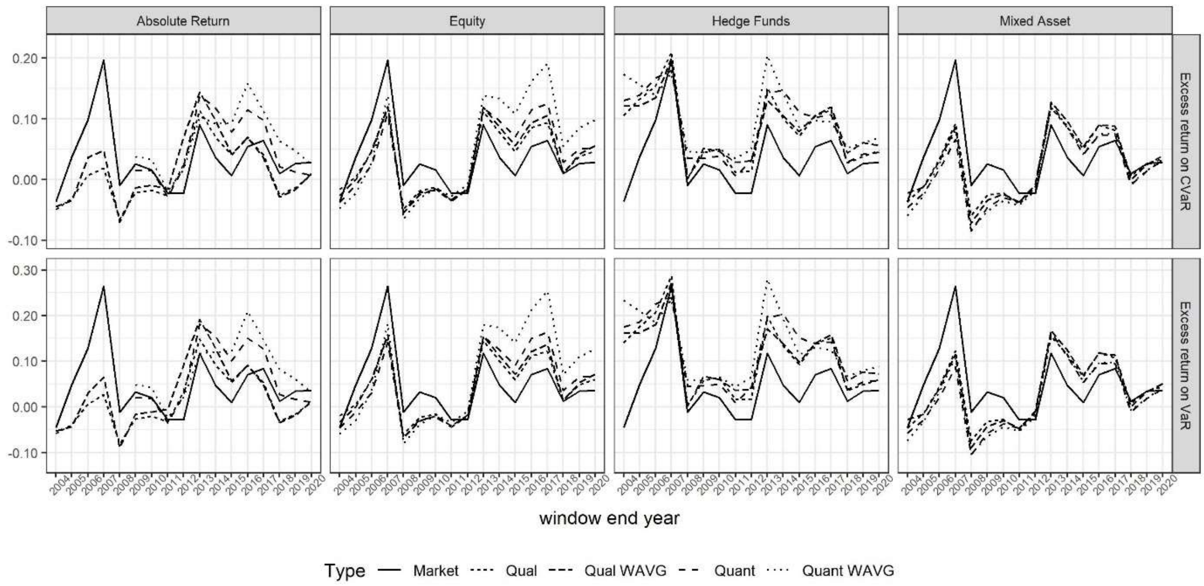

Fig. 7.19. The average excess return on VaR and the average excess return on CVaR calculated for monthly returns in each time window, calculated for the markets (Market), qualitative (Qual), and quantitative (Quant) funds, as well as the average excess return on VaR and the average excess return on CVaR calculated for monthly returns in each time window weighted by the total net assets of qualitative (Qual WAVG) and quantitative (Quant WAVG) funds, divided into selected four main strategies according to the LGC scheme. Source: Author's own study

Table 7.8. summarizes the results presented in Figure 7.19. The results of a pairwise comparison presented in Table 7.8. allow for drawing conclusions similar to those drawn in the case of CAPM-based measures. Again, in the case of absolute return and equity funds, quant funds outperformed qualitative funds more frequently. However, quant absolute return funds outperformed qualitative funds in a less systematic manner compared to classic CAPM-based measures. On the other hand, when comparing the results of the VaR-based measures to the results of the classic CAPM-based measures, quant hedge funds did a little better in this matter. Similarly as in the case of the classic CAPM-based measures, quant absolute return, equity, and hedge funds more frequently outperformed the market. Again, in the group of mixed asset funds, quant funds turned out to be systematically outperformed by qualitative funds and more often outperformed by the market. It is also worth adding that taking into account absolute return and equity funds, similarly as in the case of the overall sample and classic CAPM-based measures, TNA was more positively related to performance in the group of quantitative funds

compared to qualitative funds. When it comes to hedge and mixed asset funds, this relationship was similar in both groups.

Measures based on value at risk (VaR) - Absolute Return					
	Losers				
Group	Market	Qual	Qual_WAVG	Quant	Quant_WAVG
Market		0.71	0.65	0.42	0.12
Qual	0.29		0.35	0.25	0.17
Qual_WAVG	0.35	0.65		0.33	0.33
Quant	0.58	0.75	0.67		0.25
Quant_WAVG	0.88	0.83	0.67	0.75	

Measures based on value at risk (VaR) - Equity					
	Losers				
Group	Market	Qual	Qual_WAVG	Quant	Quant_WAVG
Market		0.41	0.41	0.47	0.47
Qual	0.59		0.35	0.47	0.35
Qual_WAVG	0.59	0.65		0.53	0.29
Quant	0.53	0.53	0.44		0.24
Quant_WAVG	0.53	0.65	0.71	0.76	

Measures based on value at risk (VaR) - Hedge Funds					
	Losers				
Group	Market	Qual	Qual_WAVG	Quant	Quant_WAVG
Market		0	0	0.06	0.06
Qual	1		0.35	0.44	0.29
Qual_WAVG	1	0.65		0.53	0.26
Quant	0.94	0.56	0.47		0.35
Quant_WAVG	0.94	0.71	0.74	0.65	

Measures based on value at risk (VaR) - Mixed Asset					
	Losers				
Group	Market	Qual	Qual_WAVG	Quant	Quant_WAVG
Market		0.53	0.53	0.59	0.59
Qual	0.47		0.5	0.82	0.91
Qual_WAVG	0.47	0.5		0.88	1
Quant	0.41	0.18	0.12		0.41
Quant_WAVG	0.41	0.09	0	0.59	

Tab. 7.8. The results of a pairwise comparison that indicate the percentage of cases (time windows) in which one group (rows) performed better than another one (columns) according to both the average excess return on VaR and the average excess return on CVaR, divided into selected four main strategies according to the LGC scheme. Source: Author's own study

Results by region

This section aims to answer a supplementary research question of whether differences in performance between quantitative and qualitative funds differ between the groups of funds distinguished in terms of the region of a primary investment focus. Figure 7.20. presents the average results for four most numerous groups of funds distinguished in terms of the region of a primary investment focus. Clearly observable better results of quant funds in comparison with qualitative funds can be spotted in the group of funds primarily investing in the region of Eastern Asia. In the group of funds primarily investing in Northern America, all fund categories had a similar average performance except for the TNA-weighted quant category, which outperformed other fund categories and the market. This suggests that larger quantitative funds performed substantially better compared to smaller quant funds. In the case of the groups of funds primarily investing in Northern Europe and Western Europe, differences between the average performance of quantitative and qualitative funds were not so clear. However, in the case of both regions, qualitative funds managing larger TNA seemed to outstand negatively. Additionally, in the case of funds primarily investing in Western Europe, all fund categories appeared to be clearly outperformed by the market. The results presented in Figure 7.20. allow for drawing similar conclusions to those drawn from previously discussed performance measures, although they share the biggest similarities with the Sharpe ratio. Most of all, the results confirm previously drawn conclusions that the average performance differs between the regions.

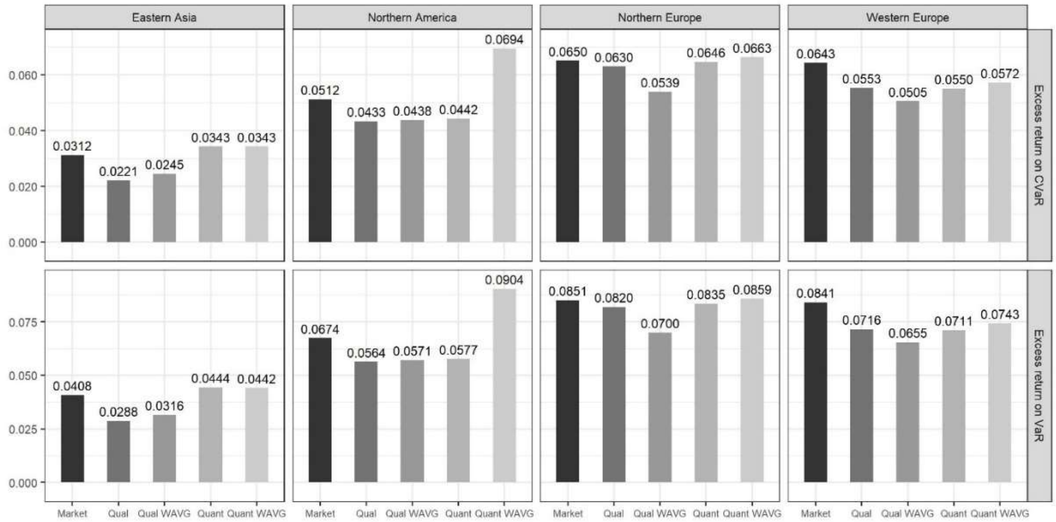

Fig. 7.20. The average excess return on VaR and the average excess return on CVaR calculated for monthly returns in all rolling windows of the markets (Market), qualitative (Qual), and quantitative (Quant) funds, as well as the average excess return on VaR and the average excess return on CVaR calculated for monthly returns in all rolling windows weighted by total the net assets of qualitative (Qual WAVG) and quantitative (Quant WAVG) funds, in the entire research period from 01/01/2000 to 31/12/2020, divided into four most numerous regions of primary investment focus. Source: Author's own study

The behaviour of the results of the VaR-based performance measures over the time windows is presented in Figure 7.21. The indications of both VaR-based measures are marked by a high level of consistency, which is higher compared to the level of consistency of CAPM-based measures. Similarly as in the case of previously discussed results pertaining to VaR-based performance measures, the results presented in Figure 7.21. are similar to the ones received for the classic CAPM-based performance measures (especially the Sharpe ratio) and allow for drawing similar conclusions.

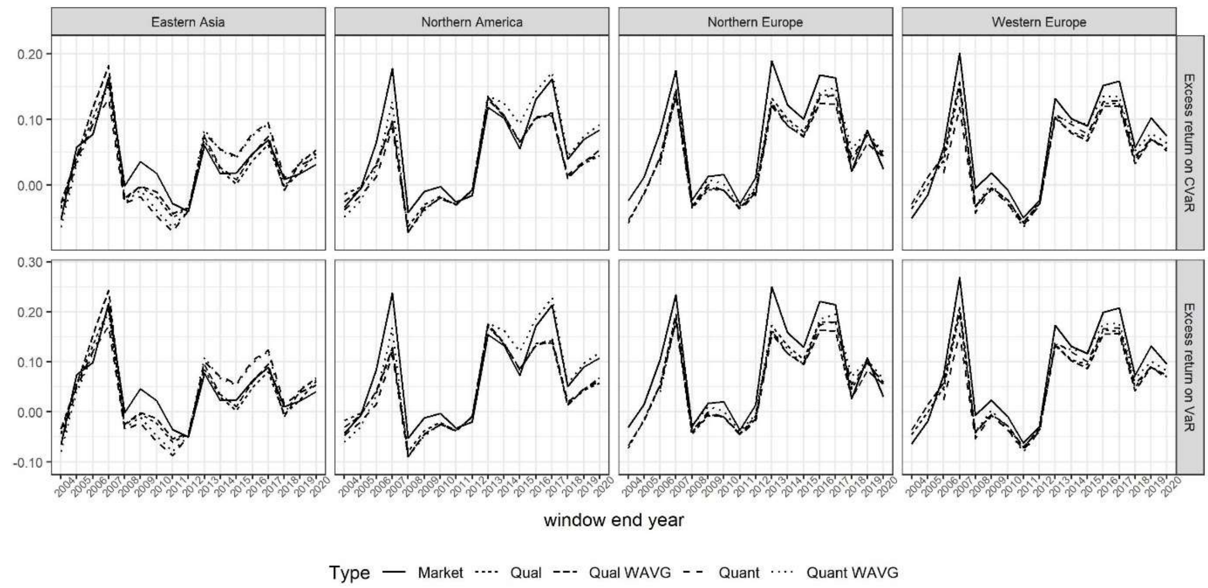

Fig. 7.21. The average excess return on VaR and the average excess return on CVaR calculated for monthly returns in each time window, calculated for the markets (Market), qualitative (Qual), and quantitative (Quant) funds, as well as the average excess return on VaR and the average excess return on CVaR calculated for monthly returns in each time window weighted by the total net assets of qualitative (Qual WAVG) and quantitative (Quant WAVG) funds, divided into four most numerous regions of primary investment focus. Source: Author's own study

Moving to a pairwise comparison of the average results over the time windows from Figure 7.21., Table 7.9. also seems to confirm that the results for the VaR-based measures are similar to those obtained for the CAPM-based measures, allowing to draw similar conclusions. The low differences in percentages do not allow for changing general conclusions drawn in the interpretation of the results presented in the pairwise comparison of the results for CAPM-based measures (see Table 7.6.).

Measures based on value at risk (VaR) - Eastern Asia					
	Losers				
Group	Market	Qual	Qual_WAVG	Quant	Quant_WAVG
Market		0.59	0.47	0.35	0.47
Qual	0.41		0.06	0.59	0.53
Qual_WAVG	0.53	0.94		0.65	0.59
Quant	0.65	0.41	0.35		0.5
Quant_WAVG	0.53	0.47	0.41	0.47	

Measures based on value at risk (VaR) - Northern America					
	Losers				
Group	Market	Qual	Qual_WAVG	Quant	Quant_WAVG
Market		0.65	0.71	0.76	0.47
Qual	0.35		0.44	0.71	0.41
Qual_WAVG	0.29	0.5		0.65	0.35
Quant	0.24	0.29	0.32		0.21
Quant_WAVG	0.53	0.59	0.65	0.76	

Measures based on value at risk (VaR) - Northern Europe					
	Losers				
Group	Market	Qual	Qual_WAVG	Quant	Quant_WAVG
Market		0.88	0.88	0.87	0.8
Qual	0.12		0.65	0.63	0.27
Qual_WAVG	0.12	0.35		0.47	0.13
Quant	0.13	0.37	0.53		0.13
Quant_WAVG	0.2	0.73	0.87	0.87	

Measures based on value at risk (VaR) - Western Europe					
	Losers				
Group	Market	Qual	Qual_WAVG	Quant	Quant_WAVG
Market		0.88	0.88	1	0.93
Qual	0.12		0.47	0.6	0.27
Qual_WAVG	0.12	0.53		0.53	0.33
Quant	0	0.4	0.47		0.2
Quant_WAVG	0.07	0.73	0.67	0.8	

Tab. 7.9. The results of a pairwise comparison that indicate the percentage of cases (time windows) in which one group (rows) performed better than another one (columns) according to both the average excess return on VaR and the average excess return on CVaR, divided into four most numerous regions of primary investment focus. Source: Author's own study

7.4. Measures based on lower partial moments (LPM)

Overall results

The next results pertain to a group of selected LPM-based portfolio performance measures commonly applied in the studies on the performance of investment funds. This group of portfolio performance measures was presented in Section 4.1.3. The analysis of the results may be more demanding this time due to the application of as many as 3 different portfolio performance measures namely, the Omega ratio (Shadwick & Keating, 2002; Kaplan & Knowles, 2004), the Sortino ratio (Sortino & van der Meer, 1991), and the Kappa3 ratio (Kaplan & Knowles, 2004). They were expressed with formulas 4.24., 4.25., and 4.27., respectively.

Figure 7.22. presents the average results obtained for the Kappa3, Omega, and Sortino ratios taking into account all windows tested in the entire research period from 01/01/2000 to 31/12/2020. The results of the three LPM-based measures suggest that on average quant funds outperform the market and qualitative funds. This especially refers to quantitative funds managing larger TNA. It should be mentioned that the indications of the results obtained for the Omega ratio slightly differ from the indications of the results obtained for the other two LPM-based measures. Namely, according to the Omega ratio, the advantage of quantitative

funds over qualitative funds and the market is much lower compared to other LPM-based ratios. It suggests that the advantage of quant funds is not that significant in terms of the excess returns over the benchmark (equity market) to average returns falling below the benchmark. Nevertheless, the results obtained for LPM-based measures, especially for the Kappa3 and Sortino ratios, allow for drawing conclusions similar to those drawn from the results obtained for previously discussed relative measures of portfolio performance. It is in line with findings of Eling and Schuhmacher (2007), Eling (2008), Ornelas, Silva and Fernandes (2012), as well as Zakamouline (2010), who proposed that different relative portfolio performance measures allow for developing similar rankings. The results obtained so far suggest that portfolio management skills related to returns variability and systematic risk management on average go hand in hand with tail risk and adverse-returns-related risk management.

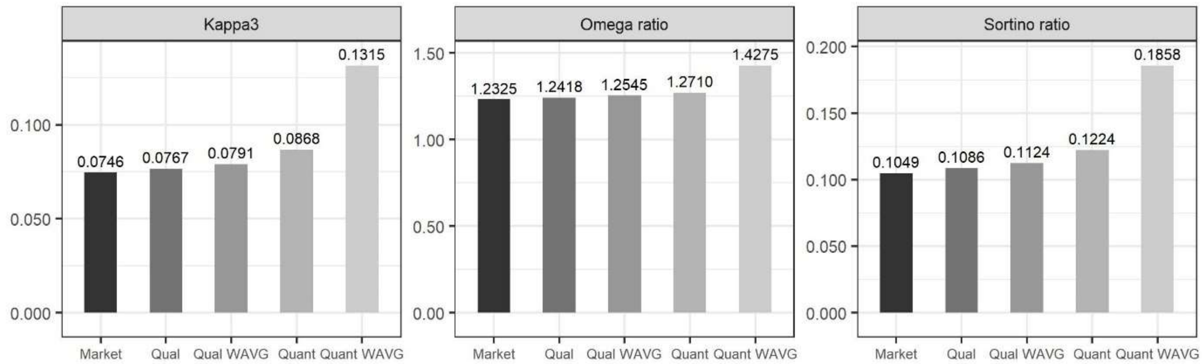

Fig. 7.22. The average Omega, Sortino, and Kappa3 ratios calculated for monthly returns in all rolling windows of the markets (Market), qualitative (Qual), and quantitative (Quant) funds, as well as the average Omega, Sortino, and Kappa3 calculated for monthly returns in all rolling windows weighted by the total net assets of qualitative (Qual WAVG) and quantitative (Quant WAVG) funds, in the entire research period from 01/01/2000 to 31/12/2020. Source: Author's own study

Moving to the homogeneity of the results obtained for the LPM-based performance measures, Figure 7.23. suggests that there are some slight differences between quantitative and qualitative funds in terms of interquartile range. Similar conclusions could be drawn in the case of the Sharpe ratio and VaR-based measures. Quant funds differ from qualitative funds mostly in terms of the 75th percentile, which is higher for quant funds. It indicates that the upper 25% of observations of the LPM-based measures in quant group have higher values. Differences in the 75th percentiles contribute the most to differences in spreads between the fund types (quantitative/qualitative).

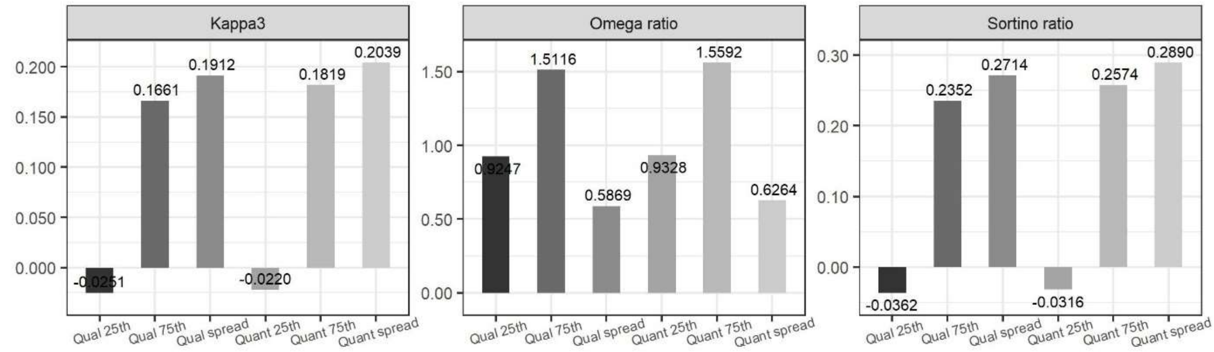

Fig. 7.23. The 25th and 75th percentile of the average Omega, Sortino, and Kappa3 ratios, as well as spread between these percentiles, calculated for all rolling windows of qualitative (Qual) and quantitative (Quant) funds in the entire research period from 01/01/2000 to 31/12/2020. Source: Author's own study

Figure 7.24. presents the behaviour of the average results obtained for LPM-based measures over the time windows. The results obtained allow for stating that the applied LPM-based performance measures are marked by high consistency in terms of conclusions they allow to make. Slight differences between the Omega ratio and the other two LPM-based measures, which could be observed in Figure 7.22., are hardly observable in the case of the results presented in Figure 7.24. The underperformance of larger quant funds captured by the Omega ratio and presented in Figure 7.22. may be related to their lower performance in the window ending in 2007. Figure 7.24. suggests that again, in the case of the Kappa3, Omega, and Sortino ratios, the results obtained allowed for drawing conclusions similar to those drawn from previously discussed performance measures. They shared some common major features. The market systematically outperformed all fund categories by the window ending in 2011-2012, and then it was mostly outperformed by the other fund categories (especially by the TNA-weighted quant fund category). All fund categories reached the lowest levels of performance in the window ending in 2008. Their average performance also behaved similarly over the time windows, suggesting positive correlations between the performance levels of fund categories.

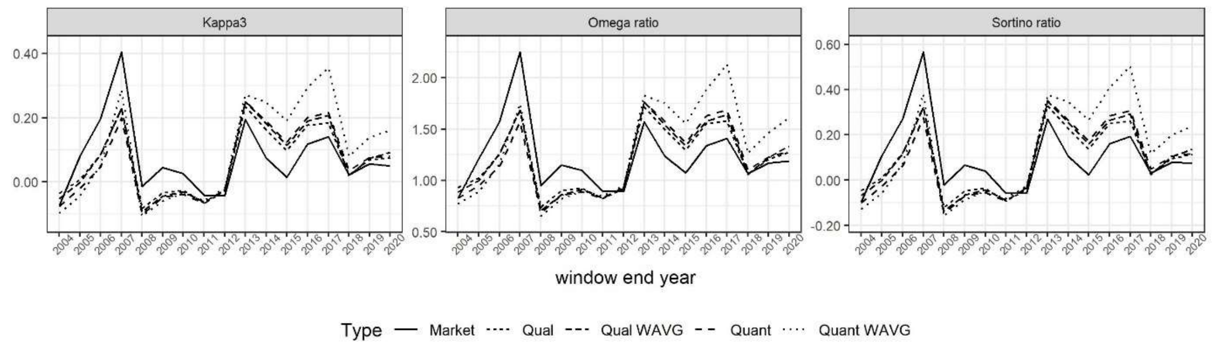

Fig. 7.24. The average Omega, Sortino, and Kappa3 ratios calculated for monthly returns in each time window of the markets (Market), qualitative (Qual), and quantitative (Quant) funds, as well as the average Omega, Sortino, and Kappa3 ratios calculated for monthly returns in each time window weighted by the total net assets of qualitative (Qual WAVG) and quantitative (Quant WAVG) funds. Source: Author's own study

Table 7.10. constitutes a summary of the results presented in Figure 7.24. According to the results of a pairwise comparison of categories, which aimed to indicate a percentage of

winning cases for each pair, all fund categories managed to outperform the market slightly more often than in 50% of cases. The percentages of cases where quant and qual funds outperformed each other were similar, i.e., around 50%. Nevertheless, when considering the TNA-weighted categories, quant funds outperformed qualitative funds more often. Larger funds (in terms of TNA managed) outperformed smaller funds more often in the groups of quantitative and qualitative funds; however, this phenomenon appeared to be stronger in the group of quantitative funds. It may suggest that a positive relationship between TNA under management and performance is stronger in the group of quant funds. Similar conclusions could be drawn in the case of previously discussed relative measures of portfolio performance.

Measures based on lower partial moments (LPM) - Overall results					
	Losers				
Group	Market	Qual	Qual_WAVG	Quant	Quant_WAVG
Market		0.45	0.47	0.47	0.47
Qual	0.53		0.39	0.45	0.35
Qual_WAVG	0.53	0.61		0.53	0.35
Quant	0.53	0.55	0.47		0.24
Quant_WAVG	0.53	0.65	0.65	0.76	

Tab. 7.10. The results of a pairwise comparison that indicate the percentage of cases (time windows) in which one group (rows) performed better than another one (columns) according to all applied measures based on lower partial moments (LPM). Source: Author's own study

Results by strategy

This section refers to a supplementary research question of whether differences in performance between quantitative and qualitative funds differ between the groups of funds distinguished in terms of strategy. Figure 7.25. presents the results obtained for LPM-based measures broken down to selected four main strategies according to the Lipper Global Classification scheme. According to the results presented in Figure 7.25., similarly as in the case of previously discussed relative measures of portfolio performance, quant funds (especially the ones with larger TNA) appear to outperform the market and qualitative funds in the groups of absolute return, equity, and hedge funds. In the case of the mixed asset funds the opposite is true and quant funds appear to perform worse compared to market and qualitative funds; nevertheless, the differences are not so high. When it comes to hedge funds, the advantage of quantitative funds over qualitative funds was not as clear as in the groups of absolute return and equity funds.

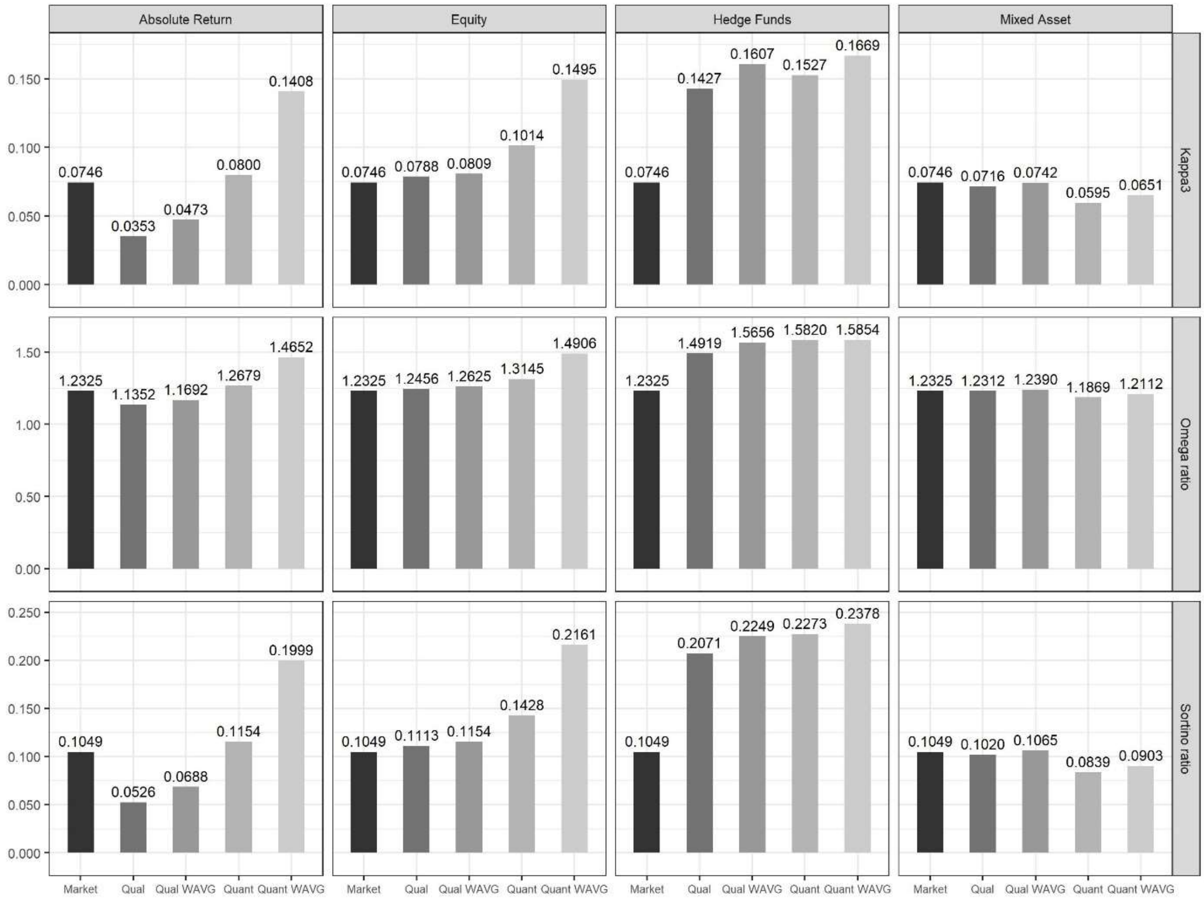

Fig. 7.25. The average Omega, Sortino, and Kappa3 ratios calculated for monthly returns in all rolling windows of the markets (Market), qualitative (Qual), and quantitative (Quant) funds, as well as the average Omega, Sortino, and Kappa3 ratios calculated for monthly returns in all rolling windows weighted by the total net assets of qualitative (Qual WAVG) and quantitative (Quant WAVG) funds, in the entire research period from 01/01/2000 to 31/12/2020, divided into selected four main strategies according to the LGC scheme. Source: Author's own study

Again, the highest positive impact of the application of the quantitative portfolio management process on performance can be observed in the group of absolute return funds. Surprisingly, after accounting for risk, quant absolute return funds on average outperformed qualitative equity funds and all categories of mixed asset funds. Mixed asset and equity funds generated significantly higher unadjusted returns compared to absolute return funds. However, they are much more risky in terms of any kind of risk taken into account by the relative measures of portfolio performance discussed so far. Slightly lower but still significant and positive impact of the application of the quantitative portfolio management process can be observed in the group of equity funds. The lowest impact can be observed in the groups of hedge and mixed asset funds; however, in the group of hedge funds the impact was positive and in the group of mixed asset funds the impact was negative.

Similarly as in the case of the overall results, the least differences between the categories can be observed in the case of the Omega ratio. The Omega ratio appeared to capture the lowest impact of the application of the quantitative portfolio management process on funds performance. Nevertheless, the average values of the Omega ratio still allowed to draw conclusions quite similar to those drawn from the results of the other LPM-based measures, at least in terms of the order of the best performing categories.

The behaviour of the results obtained for the LPM-based performance measures presented in Figure 7.26. is similar to the behaviour of the results obtained in the case of previously discussed relative measures of portfolio performance. It is similar especially to the behaviour of the Sharpe ratio and VaR-based portfolio performance measures. The results received for the aforementioned measures discussed earlier share some major features with the results for the LPM-based measures. However, there is also a clear difference, i.e., an outstandingly high average performance of quant funds in the window ending in 2013 in the group of hedge funds that can be observed in all three LPM-based measures. Taking into account the values of previously discussed performance measures for this group in the same window, quant hedge funds in the window ending in 2013, could be exposed to a very low risk related to the adverse returns compared to other windows. It is puzzling why it was not observable in the case of VaR-based measures, which took into account a tail risk.

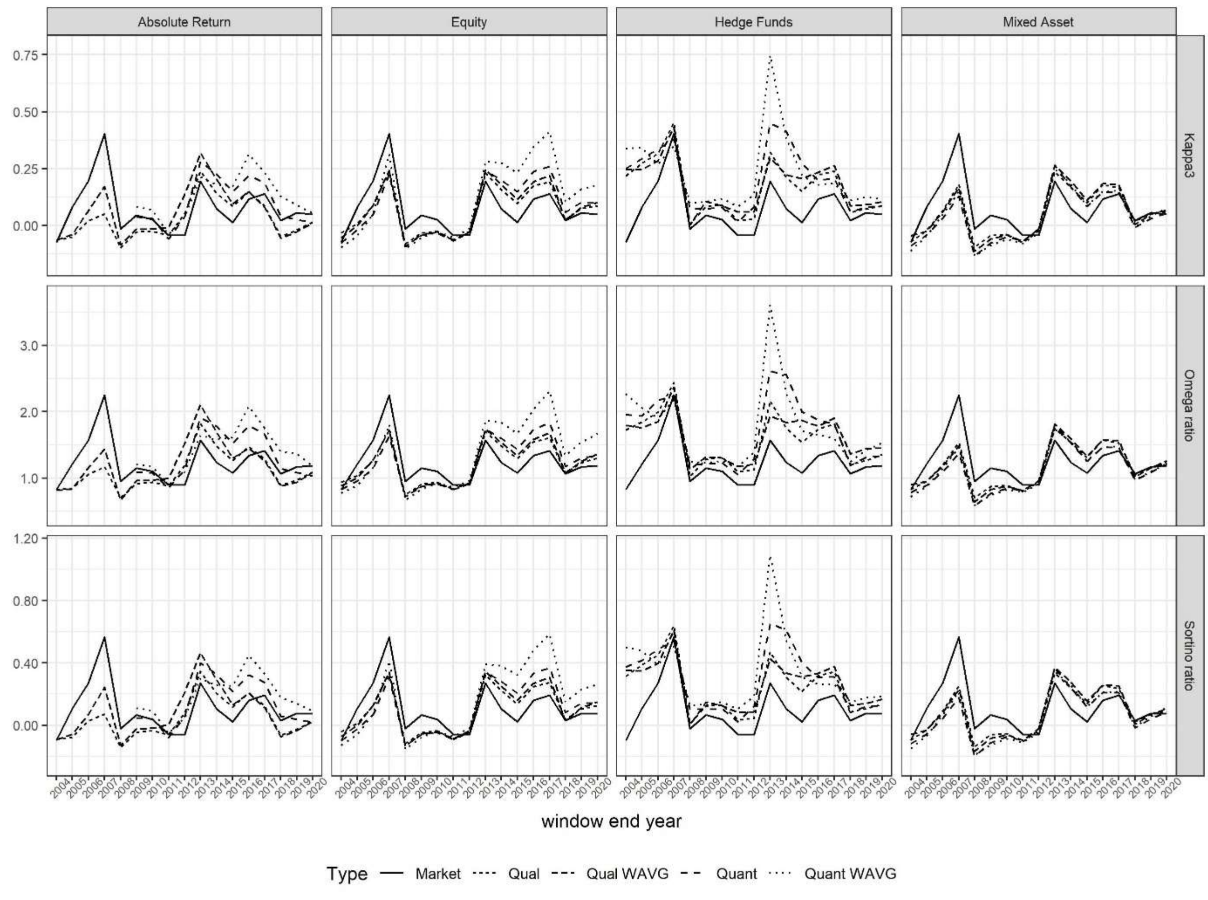

Fig. 7.26. The average Omega, Sortino, and Kappa3 ratios calculated for monthly returns in each time window, calculated for the markets (Market), qualitative (Qual), and quantitative (Quant) funds, as well as the average Omega, Sortino, and Kappa3 ratios calculated for monthly returns in each time window weighted by the total net assets of qualitative (Qual WAVG) and quantitative (Quant WAVG) funds, divided into selected four main strategies according to the LGC scheme. Source: Author's own study

Table 7.11. summarizes the results presented in Figure 7.26. in the form of a pairwise comparison of the average results calculated for each category. According to Table 7.11., the

results obtained allow for drawing similar conclusions as in the case of previously discussed relative measures of portfolio performance. The repeating results across different types of relative measures confirm a more frequent advantage of quantitative funds over qualitative funds in the groups of the absolute return, equity, and hedge funds, where quantitative funds outperform qualitative funds more frequently especially after accounting for TNA. Similarly as in the case of previously discussed relative performance measures, the reverse situation can be observed in the group of mixed asset funds, in which the qualitative funds more systematically outperformed quantitative funds.

Measures based on lower partial moments (LPM) - Absolute Return					
	Losers				
Group	Market	Qual	Qual_WAVG	Quant	Quant_WAVG
Market		0.67	0.61	0.36	0.03
Qual	0.33		0.31	0.22	0.17
Qual_WAVG	0.39	0.69		0.31	0.33
Quant	0.64	0.78	0.69		0.25
Quant_WAVG	0.97	0.83	0.67	0.75	

Measures based on lower partial moments (LPM) - Equity					
	Losers				
Group	Market	Qual	Qual_WAVG	Quant	Quant_WAVG
Market		0.41	0.41	0.45	0.47
Qual	0.59		0.35	0.47	0.35
Qual_WAVG	0.59	0.63		0.57	0.29
Quant	0.55	0.53	0.43		0.24
Quant_WAVG	0.53	0.65	0.71	0.76	

Measures based on lower partial moments (LPM) - Hedge Funds					
	Losers				
Group	Market	Qual	Qual_WAVG	Quant	Quant_WAVG
Market		0	0	0.06	0.06
Qual	1		0.33	0.43	0.27
Qual_WAVG	1	0.67		0.51	0.37
Quant	0.94	0.57	0.49		0.35
Quant_WAVG	0.94	0.73	0.63	0.65	

Measures based on lower partial moments (LPM) - Mixed Asset					
	Losers				
Group	Market	Qual	Qual_WAVG	Quant	Quant_WAVG
Market		0.53	0.53	0.59	0.59
Qual	0.47		0.49	0.78	0.86
Qual_WAVG	0.47	0.51		0.88	0.96
Quant	0.41	0.22	0.12		0.41
Quant_WAVG	0.41	0.14	0.04	0.59	

Tab. 7.11. The results of a pairwise comparison that indicate the percentage of cases (time windows) in which one group (rows) performed better than another one (columns) according to all applied measures based on lower partial moments (LPM), divided into selected four main strategies according to the LGC scheme. Source: Author's own study

Results by region

This section refers to a supplementary research question pertaining to differences between regions in terms of differences between the performance of quantitative and qualitative funds. Figure 7.27. presents the average results obtained for the three LPM-based portfolio performance measures for four most numerous groups of funds distinguished in terms of the region of a primary investment focus. The results presented in Figure 7.27. take into account the entire research period. A clear average outperformance of qualitative funds by quantitative funds can be observed in the group of funds primarily investing in Eastern Asia. Nevertheless, the outperformance of the market by quant funds in this group was not so clear. The average performance of quantitative funds primarily investing in the region of Eastern Asia was also not high enough to outperform any category from the other regions. In this region, the average performance of all categories was the lowest among all four groups (regions) examined.

In the group of funds primarily investing in Northern America, the fund categories had a similar average performance. However, it was lower compared to the market. The TNA-weighted quant fund category constituted an exception in this matter. Larger quant funds appeared to significantly outperform the market and other fund categories on the average basis. The TNA-weighted quant fund category in the group of funds primarily investing in Northern America also outperformed all qualitative fund categories from any other group compared (region). However, even higher average result was obtained by the TNA-weighted quant fund category in the group of funds primarily investing in Northern Europe. A group of funds primarily investing in Northern Europe was also marked by the highest results among all groups (regions) examined. In this group, quant funds also outperformed qualitative funds; however, differences between their non-weighted average performance were not that clear. More significant differences in favour of quantitative funds occurred when the TNA-weighted average results were taken into account. In the case of the group of funds primarily investing in Western Europe, a similar situation occurred; however, general differences between quant and qual funds were even more slight.

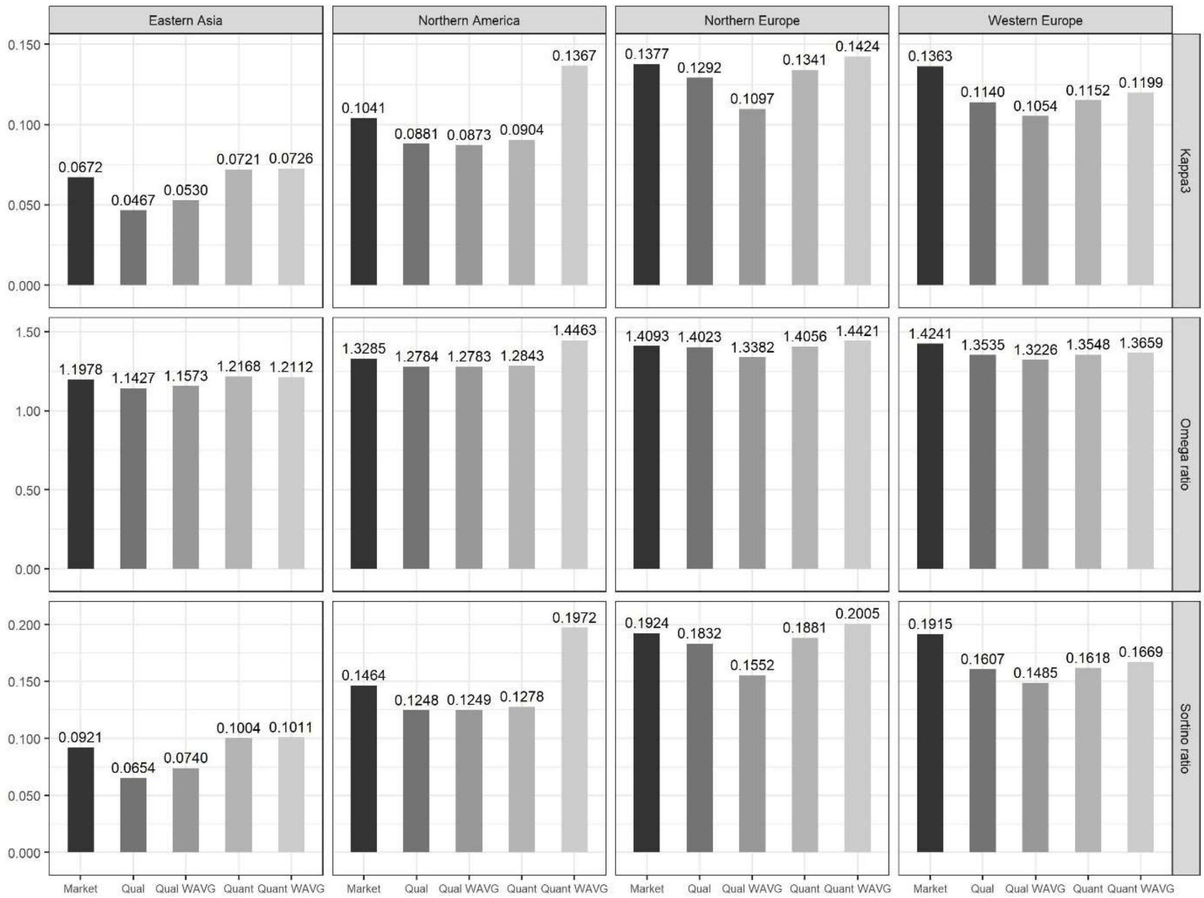

Fig. 7.27. The average Omega, Sortino, and Kappa3 ratios calculated for monthly returns in all rolling windows of the markets (Market), qualitative (Qual), and quantitative (Quant) funds, as well as the average Omega, Sortino, and Kappa3 ratios calculated for monthly returns in all rolling windows weighted by the total net assets of qualitative (Qual WAVG) and quantitative (Quant WAVG) funds, in the entire research period from 01/01/2000 to 31/12/2020, divided into four most numerous regions of primary investment focus. Source: Author's own study

In general, when it comes to the results presented in Figure 7.27., they allow to draw similar conclusions to those drawn on the basis of previously discussed relative measures of portfolio performance, especially the Sharpe ratio and VaR-based ratios. The indications of the results obtained for each of the three LPM-based measures are similar; nevertheless, the differences between the examined categories according to the Omega ratio are slightly lower compared to the other two measures from this group. A similar phenomenon could be observed in the case of the results for the overall sample and the results divided into strategies.

Figure 7.28. shows the behaviour of the LPM-based portfolio performance measures over the time windows. The results presented in Figure 7.28. allow for drawing similar conclusions as in the case of previously discussed relative performance measures, especially the Sharpe ratio and VaR-based ratios. The indications of the results calculated for each of the three LPM-based measures are similar. Slight differences between the results of the Omega ratio and the other two LPM-based measures, which were observed and discusser earlier, do not appear to constitute a problem when it comes to consistency of the results presented in Figure 7.28.

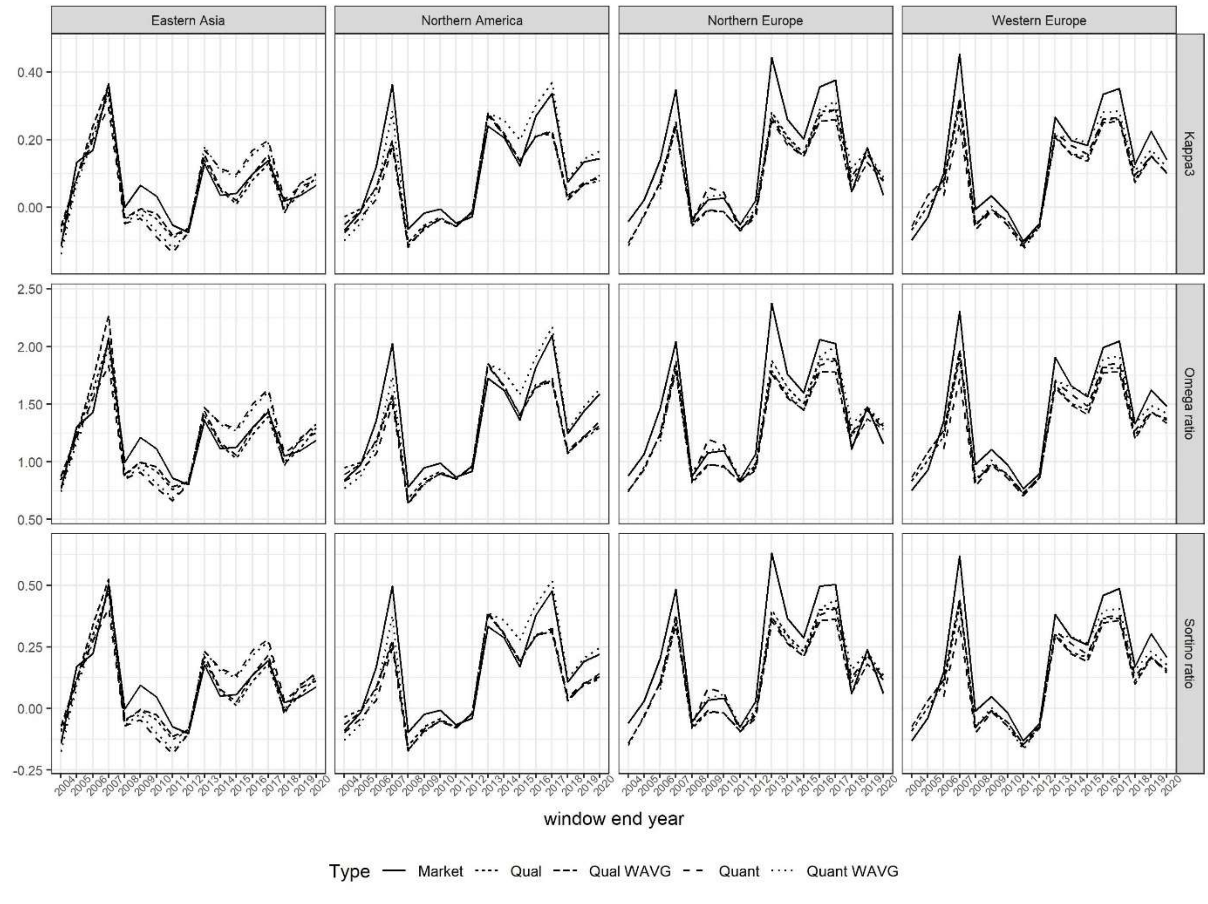

Fig. 7.28. The average Omega, Sortino, and Kappa3 ratios calculated for monthly returns in each time window, calculated for the markets (Market), qualitative, (Qual) and quantitative (Quant) funds, as well as the average Omega, Sortino, and Kappa3 ratios calculated for monthly returns in each time window weighted by the total net assets of qualitative (Qual WAVG) and quantitative (Quant WAVG) funds, divided into four most numerous regions of primary investment focus. Source: Author's own study

Table 7.12. makes an attempt to summarise the results presented in Figure 7.28. in the form of a pairwise comparison of the average results calculated for each category. According to Table 7.12., the results are very similar to those obtained for the VaR-based performance measures. They allow to draw similar conclusions. Generally, when taking into account non-weighted fund categories, qualitative funds outperform quant funds more systematically across

the four groups (regions) examined. However, when looking at the TNA-weighted categories, quant funds appeared to outperform qual funds more often in all groups except for the group of funds primarily investing in Eastern Asia. Only in the group of funds primarily investing in Eastern Asia, qualitative funds and especially quantitative funds managed to develop a more systematic advantage over the market.

Measures based on lower partial moments (LPM) - Eastern Asia

	Losers				
Group	Market	Qual	Qual_WAVG	Quant	Quant_WAVG
Market		0.59	0.47	0.41	0.49
Qual	0.41		0.1	0.59	0.49
Qual_WAVG	0.53	0.9		0.65	0.59
Quant	0.59	0.41	0.35		0.53
Quant_WAVG	0.51	0.51	0.41	0.47	

Measures based on lower partial moments (LPM) - Northern America

	Losers				
Group	Market	Qual	Qual_WAVG	Quant	Quant_WAVG
Market		0.65	0.65	0.76	0.47
Qual	0.35		0.53	0.71	0.41
Qual_WAVG	0.35	0.47		0.67	0.39
Quant	0.24	0.29	0.33		0.22
Quant_WAVG	0.53	0.59	0.61	0.78	

Measures based on lower partial moments (LPM) - Northern Europe

	Losers				
Group	Market	Qual	Qual_WAVG	Quant	Quant_WAVG
Market		0.88	0.88	0.73	0.6
Qual	0.12		0.69	0.64	0.31
Qual_WAVG	0.12	0.31		0.42	0.22
Quant	0.27	0.36	0.58		0.27
Quant_WAVG	0.4	0.69	0.78	0.73	

Measures based on lower partial moments (LPM) - Western Europe

	Losers				
Group	Market	Qual	Qual_WAVG	Quant	Quant_WAVG
Market		0.88	0.88	1	0.89
Qual	0.12		0.47	0.58	0.31
Qual_WAVG	0.12	0.53		0.53	0.33
Quant	0	0.42	0.47		0.18
Quant_WAVG	0.11	0.69	0.67	0.82	

Tab. 7.12. The results of a pairwise comparison that indicate the percentage of cases (time windows) in which one group (rows) performed better than another one (columns) according to all applied measures based on lower partial moments (LPM), divided into four most numerous regions of a primary investment focus. Source: Author's own study

7.5. Measures based on maximum drawdown (MD)

Overall results

The last group of the relative measures of portfolio performance whose results will be discussed in this section applies the concept of a maximum drawdown that captures the tail risk. A theoretical background of the Calmar ratio and the Sterling ratio was discussed in Section 4.1.3. The ratios were expressed with formulas 4.20. and 4.21., respectively. The overall results obtained for the MD-based performance measures, which take into account all windows, are presented in Figure 7.29. Similarly as in the case of the overall results of the majority of previously discussed relative measures of portfolio performance (especially the Sharpe ratio, VaR-based, and LPM-based measures), the overall results obtained for the MD-based measures generally suggest that quantitative funds performed better than the market and qualitative funds. The advantage of quantitative funds over qualitative funds was especially clear after accounting for TNA. This suggests that larger quantitative funds performed especially better.

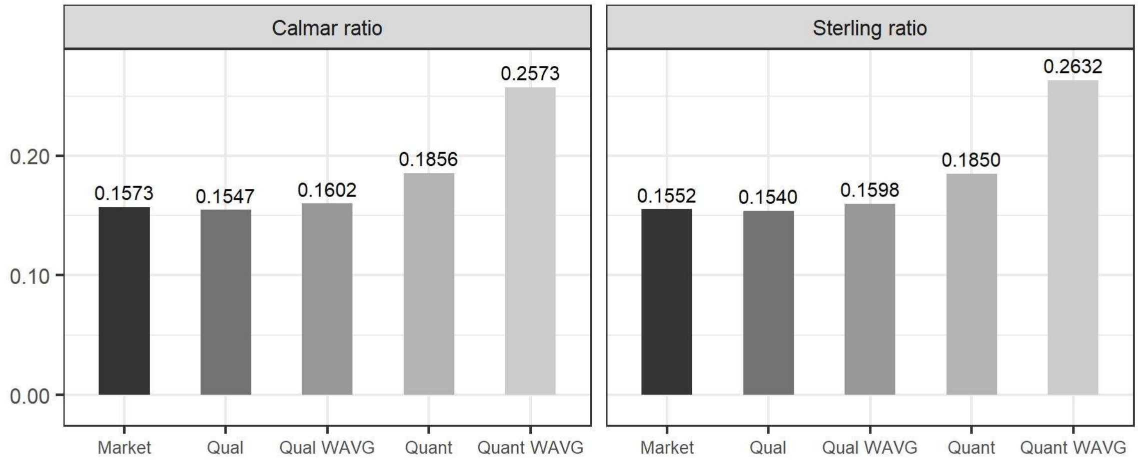

Fig. 7.29. The average Calmar and Sterling ratios calculated for monthly returns in all rolling windows of the markets (Market), qualitative (Qual), and quantitative (Quant) funds, as well as the average Calmar and Sterling ratios calculated for monthly returns in all rolling windows weighted by the total net assets of qualitative (Qual WAVG) and quantitative (Quant WAVG) funds, in the entire research period from 01/01/2000 to 31/12/2020. Source: Author's own study

According to the results obtained for the Calmar ratio (applies a maximum drawdown as a tail risk measure) and the Sterling ratio (applies the average of a specific number of the highest drawdowns as a tail risk measure), the average performance of the market and qualitative funds was very similar. Quantitative funds, especially the larger ones in terms of TNA managed, on average outperformed the market and qualitative funds. The application of different risk measures (maximum drawdown vs. the average of a specific number of the highest drawdowns) did not affect conclusions that could be drawn from the results obtained.

Regarding the homogeneity of the results obtained for quantitative and qualitative funds, according to Figure 7.30., differences in spreads between quantitative and qualitative funds appear to be slightly higher compared to previously discussed performance measures. Similarly as in the case of previously discussed measures, the main differences in spreads between quantitative and qualitative funds appear to result from the differences in the 75th percentiles. The 75th percentiles are higher in the case of quantitative funds, suggesting that the upper 25% of observations of the MD-based measures in the quant fund group have higher values. In the case of the 25th percentiles, some slight differences could also be observed. In the group of quantitative funds, the 25th percentiles were slightly higher than in the group of qualitative funds. To sum up, in the case of the MD-based measures, it is more difficult to tell that quantitative and qualitative funds are similarly homogenous. The results obtained for quantitative funds are less homogenous compared to the results obtained for qualitative funds.

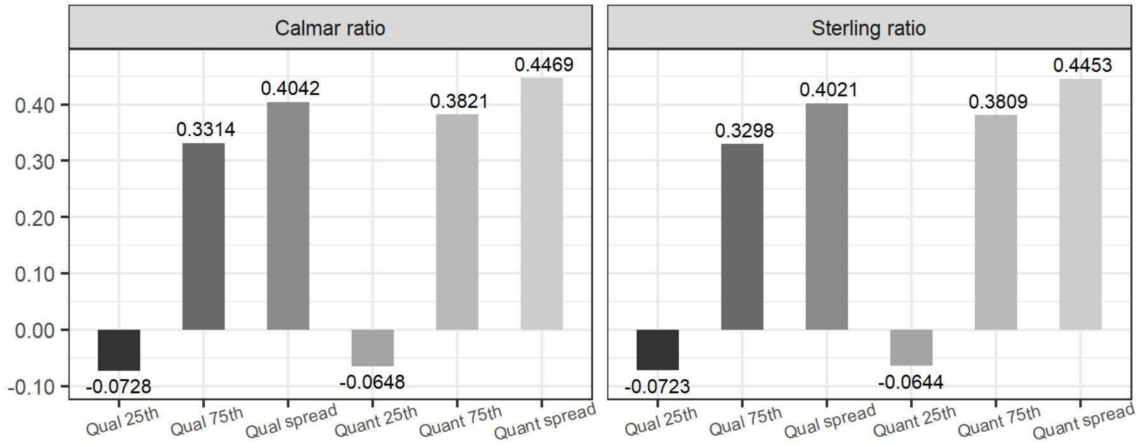

Fig. 7.30. The 25th and 75th percentile of the average Calmar and Sterling ratios, as well as spread between these percentiles, calculated for all rolling windows of qualitative (Qual) and quantitative (Quant) funds in the entire research period from 01/01/2000 to 31/12/2020. Source: Author's own study

Figure 7.31. presents the average MD-based performance measures, as well as the average MD-based performance measures weighted by TNA, calculated separately for each time window. Again, the results obtained for both MD-based performance measures over the time windows have many common features with the results obtained for previously discussed relative measures of portfolio performance. Similarly to the majority of previously discussed measures, the market systematically outperformed all fund categories by the window ending in 2011. In the following windows, the TNA-weighted quant fund category tended to outperform other categories. Performance levels were the lowest for all fund categories in the window ending in 2008. The categories also behaved similarly over the time windows, suggesting positive correlations between them.

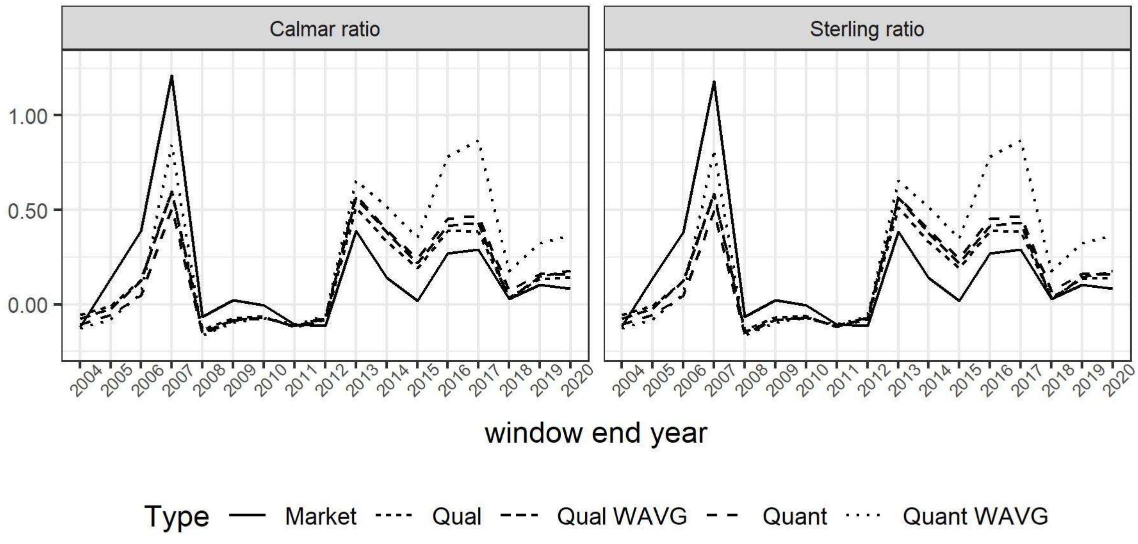

Fig. 7.31. The average Calmar and Sterling ratios calculated for monthly returns in each time window of the markets (Market), qualitative (Qual), and quantitative (Quant) funds, as well as the average Calmar and Sterling ratios calculated for monthly returns in each time window weighted by the total net assets of qualitative (Qual WAVG) and quantitative (Quant WAVG) funds. Source: Author's own study

Table 7.13. makes an attempt to briefly summarise the results presented in Figure 7.31. Referring to Table 7.13., the winning cases of qualitative and quantitative funds look similar to results obtained for previously discussed relative measures of portfolio performance that pertained to the overall sample. However, this time both fund types outperformed the market slightly more often. Also, quant funds outperformed qualitative funds slightly more systematically. It is worth noting that in the case of the results obtained for the MD-based measures, a positive relation between TNA and performance is lower for qualitative funds compared to previously discussed measures. Namely, larger qualitative funds less often outperformed the smaller ones. On the other hand, the advantage of larger quant funds over the smaller ones stays unchanged when compared to previously discussed measures.

Measures based on maximum drawdown (MD) - Overall results					
	Losers				
Group	Market	Qual	Qual_WAVG	Quant	Quant_WAVG
Market		0.41	0.41	0.41	0.41
Qual	0.59		0.47	0.41	0.35
Qual_WAVG	0.59	0.53		0.47	0.35
Quant	0.59	0.59	0.53		0.24
Quant_WAVG	0.59	0.65	0.65	0.76	

Tab. 7.13. The results of a pairwise comparison that indicate the percentage of cases (time windows) in which one group (rows) performed better than another one (columns) according to all applied measures based on maximum drawdown (MD). Source: Author's own study

Results by strategy

This section refers to a supplementary research question of whether differences in performance between quantitative and qualitative funds differ between the groups of funds distinguished in terms of strategy. The average MD-based measures broken down to strategies are presented in Figure 7.32. Generally the results allow for drawing similar conclusions as in the case of previously discussed relative measures of portfolio performance; however, some slight differences can be observed as well. Regarding similarities, in the case of absolute return and equity funds, the outperformance of qualitative funds by quantitative funds was clear, especially when considering the TNA-weighted categories. In the case of mixed asset funds, quant fund categories performed slightly worse than both qualitative fund categories and the market. In the case of hedge funds, when taking into account non-weighted average results, quant funds clearly outperformed qual funds. However, when taking into account the TNA-weighted results, quant funds performed slightly worse compared to qual funds. The TNA-weighted result for quant funds was also clearly lower than the non-weighted result for quant funds. It may suggest that on average quant funds managing larger TNA faced a higher tail risk than quant funds managing lower TNA. It is a major difference in relation to the indications of previously discussed portfolio performance measures.

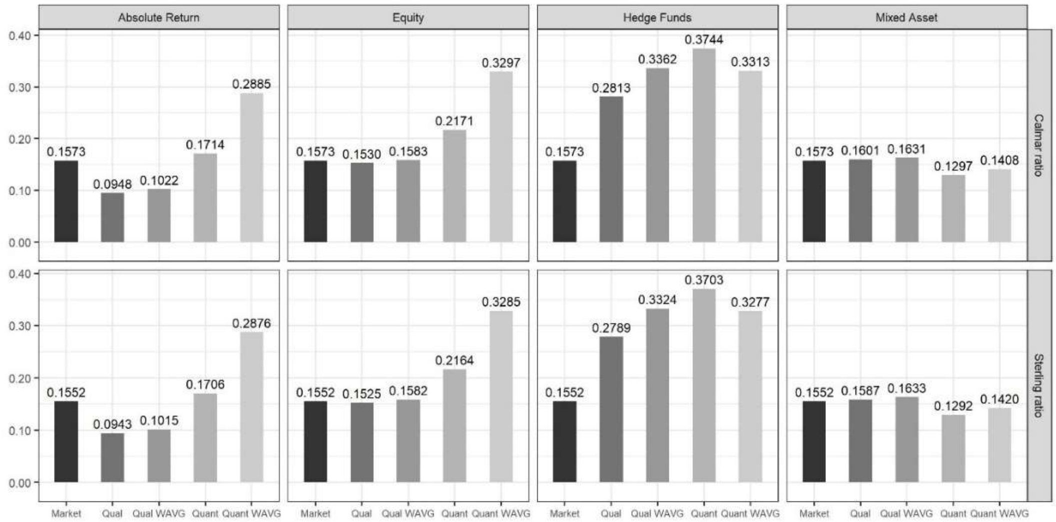

Fig. 7.32. The average Calmar and Sterling ratios calculated for monthly returns in all rolling windows of the markets (Market), qualitative (Qual), and quantitative (Quant) funds, as well as the average Calmar and Sterling ratios calculated for monthly returns in all rolling windows weighted by the total net assets of qualitative (Qual WAVG) and quantitative (Quant WAVG) funds, in the entire research period from 01/01/2000 to 31/12/2020, divided into selected four main strategies according to the LGC scheme. Source: Author's own study

Figure 7.33. presents the behaviour of the results obtained for the MD-based portfolio performance measures. The behaviour of the MD-based measures presented in Figure 7.33. resembles the behaviour of the results of previously discussed relative measures of portfolio performance. Similarly as in the case of the LPM-based portfolio performance measures, the average performance of quant funds in the group of hedge funds outstandingly increased in the window ending in 2013. Taking into account the values of previously discussed performance measures for this group in the same window, quant hedge funds in the window ending in 2013 could be exposed to a very low tail risk compared to other windows.

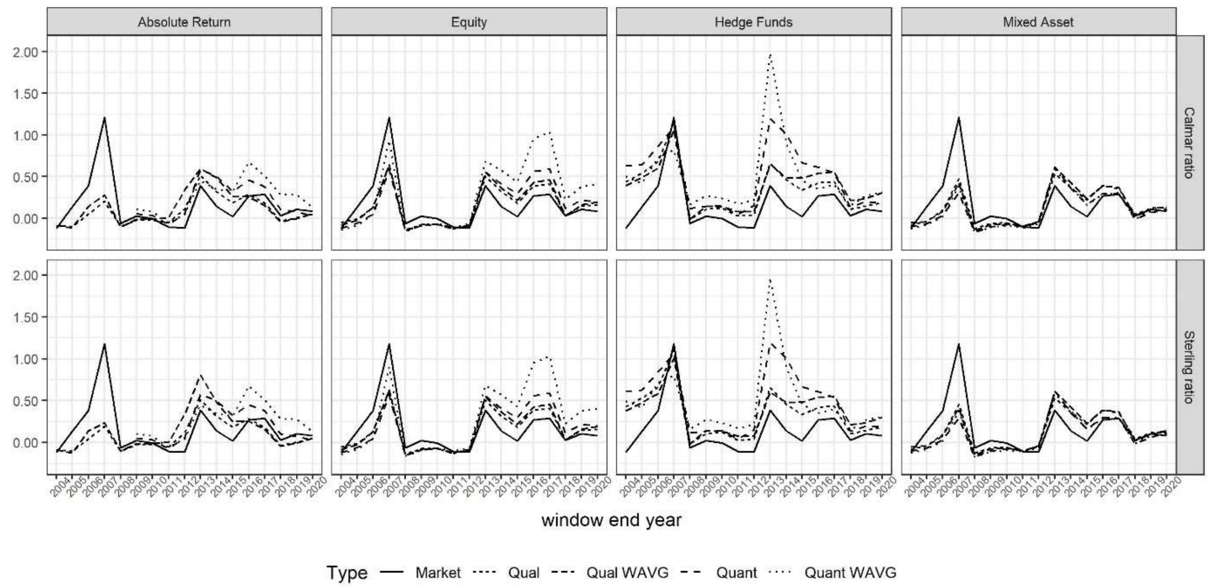

Fig. 7.33. The average Calmar and Sterling ratios calculated for monthly returns in each time window, calculated for the markets (Market), qualitative (Qual), and quantitative (Quant) funds, as well as the average Calmar and Sterling ratios calculated for monthly returns in each time window weighted by the total net assets of qualitative (Qual WAVG) and quantitative (Quant WAVG) funds, divided into selected four main strategies according to the LGC scheme. Source: Author's own study

Table 7.14. makes an attempt to summarize the results presented in Figure 7.33. Referring to Table 7.14., the results obtained for the MD-based portfolio performance measures generally allow to draw conclusions similar to those drawn from the results obtained for previously discussed relative measures of portfolio performance. Nevertheless, there are also some slight differences compared to previously discussed relative measures of portfolio performance. Namely, especially in the groups of equity and hedge funds, the number of cases in which quantitative funds outperformed qualitative funds increased. In the group of absolute return funds, this percentage slightly fell.

Measures based on maximum drawdown (MD) - Absolute Return

	Losers				
Group	Market	Qual	Qual_WAVG	Quant	Quant_WAVG
Market		0.59	0.65	0.17	0
Qual	0.41		0.41	0.25	0.25
Qual_WAVG	0.35	0.59		0.33	0.33
Quant	0.83	0.75	0.67		0.33
Quant_WAVG	1	0.75	0.67	0.67	

Measures based on maximum drawdown (MD) - Equity

	Losers				
Group	Market	Qual	Qual_WAVG	Quant	Quant_WAVG
Market		0.41	0.41	0.47	0.41
Qual	0.59		0.35	0.41	0.29
Qual_WAVG	0.59	0.65		0.47	0.29
Quant	0.53	0.59	0.53		0.24
Quant_WAVG	0.59	0.71	0.71	0.76	

Measures based on maximum drawdown (MD) - Hedge Funds

	Losers				
Group	Market	Qual	Qual_WAVG	Quant	Quant_WAVG
Market		0.06	0.06	0.06	0.06
Qual	0.94		0.29	0.12	0.24
Qual_WAVG	0.94	0.71		0.35	0.35
Quant	0.94	0.88	0.65		0.47
Quant_WAVG	0.94	0.76	0.65	0.53	

Measures based on maximum drawdown (MD) - Mixed Asset

	Losers				
Group	Market	Qual	Qual_WAVG	Quant	Quant_WAVG
Market		0.35	0.41	0.47	0.59
Qual	0.65		0.53	0.82	0.82
Qual_WAVG	0.59	0.47		0.94	0.94
Quant	0.53	0.18	0.06		0.65
Quant_WAVG	0.41	0.18	0.06	0.35	

Tab. 7.14. The results of a pairwise comparison that indicate the percentage of cases (time windows) in which one group (rows) performed better than another one (columns) according to all applied measures based on maximum drawdown (MD). Source: Author's own study

Results by region

Moving to the breakdown of the results to the regions of a primary investment focus, Figure 7.34. presents the average results obtained for four most numerous groups. Referring to Figure 7.34., the results obtained for MD-based measures generally allow to draw conclusions similar to those drawn from previously discussed relative measures of portfolio performance. Nevertheless, there are also some differences between them. The major differences refer to lower results for all categories examined in the group of Eastern Asia in the case of MD-based measures. Such results may suggest that especially this region suffered a significant exposure to tail risk. However, it is puzzling that such a decrease of performance in this region was not visible in the results obtained for VaR-based measures, i.e., other performance measures taking into account a tail risk. In addition, in the case of Northern America, the average performance of the market increased, as well as its advantage over most fund categories. As opposed to previous relative measures of portfolio performance, the TNA-weighted average results for quant funds in this region are now just slightly higher than the average results for the market.

On the other hand, in the region of Northern Europe, after accounting for the tail risk, the performance of the market decreased compared to the performance of fund categories.

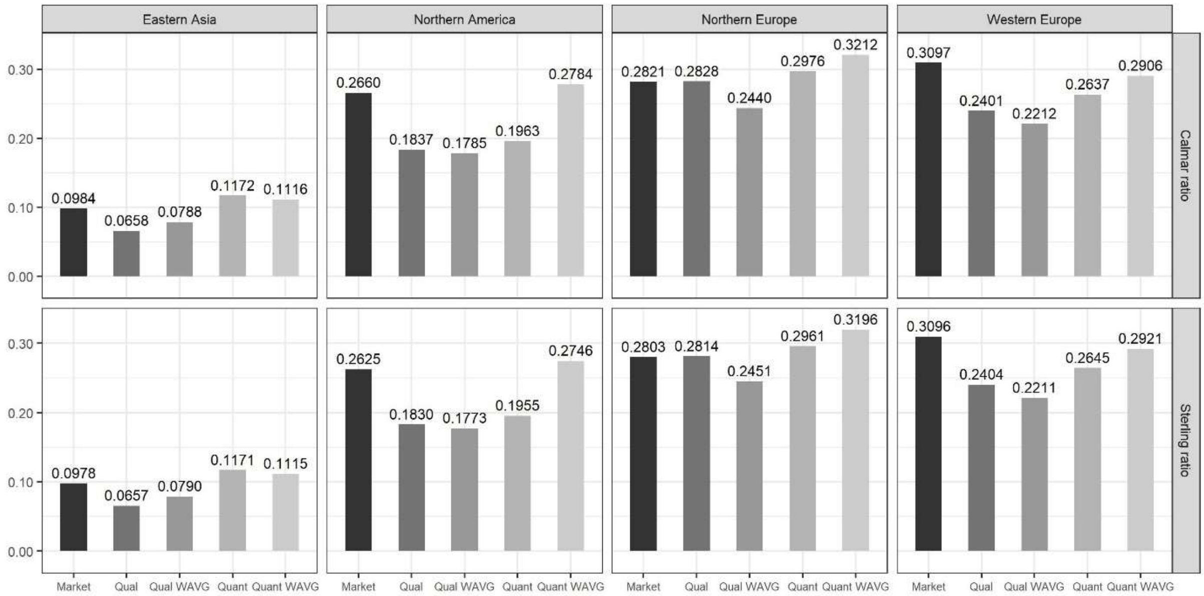

Fig. 7.34. The average Calmar and Sterling ratios calculated for monthly returns in all rolling windows of the markets (Market), qualitative (Qual), and quantitative (Quant) funds, as well as the average Calmar and Sterling ratios calculated for monthly returns in all rolling windows weighted by the total net assets of qualitative (Qual WAVG) and quantitative (Quant WAVG) funds, in the entire research period from 01/01/2000 to 31/12/2020, divided into four most numerous regions of primary investment focus. Source: Author's own study

Table 7.15. makes an attempt to summarise the results presented in Figure 7.35. Conclusions that can be made based on the results of a pairwise comparison presented in Table 7.15. are generally similar to those that could be drawn from the results obtained for previously discussed relative measures of portfolio performance. Nevertheless, there are also some differences between them. The major difference consists in the increased percentage of wins of quantitative funds over qualitative funds compared to previously discussed relative measures of portfolio performance in the case of the groups of funds primarily investing in Northern America, Northern Europe, and Western Europe. In the groups of funds primarily investing in Northern Europe and Western Europe, quantitative funds appeared to outperform qualitative funds slightly more often. In the case of previously discussed relative measures of portfolio performance, qualitative funds outperformed quantitative funds slightly more often in these groups.

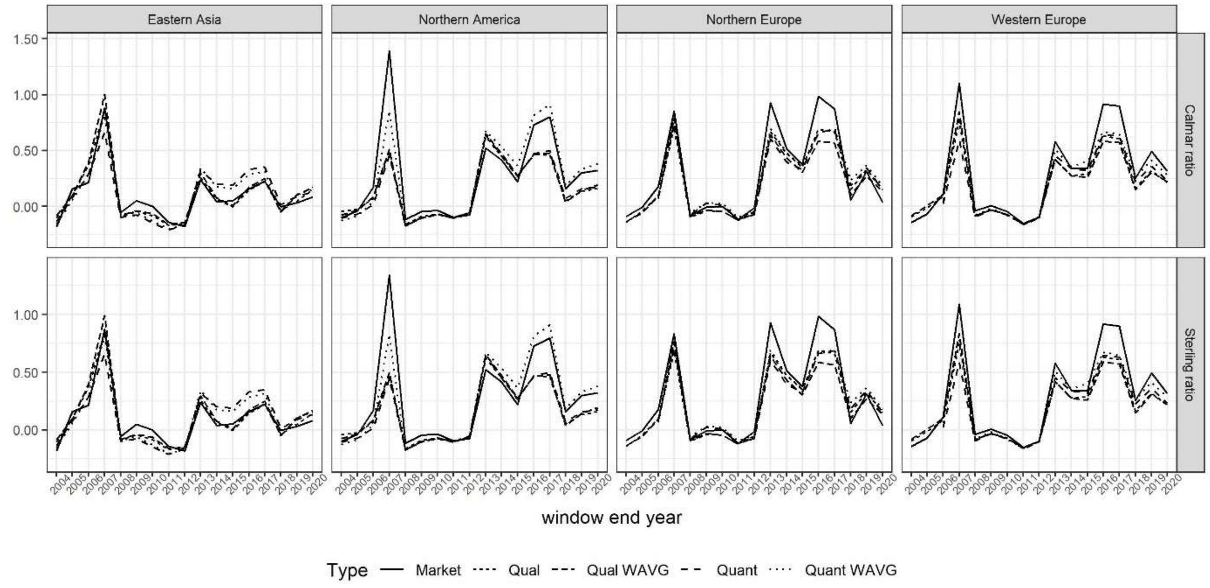

Fig. 7.35. The average Calmar and Sterling ratios calculated for monthly returns in each time window, calculated for the markets (Market), qualitative (Qual), and quantitative (Quant) funds, as well as the average Calmar and Sterling ratios calculated for monthly returns in each time window weighted by the total net assets of qualitative (Qual WAVG) and quantitative (Quant WAVG) funds, divided into four most numerous regions of primary investment focus. Source: Author's own study

Measures based on maximum drawdown (MD) - Eastern Asia					
	Losers				
Group	Market	Qual	Qual_WAVG	Quant	Quant_WAVG
Market		0.59	0.41	0.35	0.41
Qual	0.41		0.06	0.59	0.59
Qual_WAVG	0.59	0.94		0.65	0.59
Quant	0.65	0.41	0.35		0.47
Quant_WAVG	0.59	0.41	0.41	0.53	

Measures based on maximum drawdown (MD) - Northern America					
	Losers				
Group	Market	Qual	Qual_WAVG	Quant	Quant_WAVG
Market		0.65	0.65	0.76	0.47
Qual	0.35		0.53	0.53	0.41
Qual_WAVG	0.35	0.47		0.53	0.29
Quant	0.24	0.47	0.47		0.24
Quant_WAVG	0.53	0.59	0.71	0.76	

Measures based on maximum drawdown (MD) - Northern Europe					
	Losers				
Group	Market	Qual	Qual_WAVG	Quant	Quant_WAVG
Market		0.82	0.88	0.6	0.53
Qual	0.18		0.74	0.47	0.13
Qual_WAVG	0.12	0.26		0.33	0.07
Quant	0.4	0.5	0.67		0.13
Quant_WAVG	0.47	0.87	0.93	0.87	

Measures based on maximum drawdown (MD) - Western Europe					
	Losers				
Group	Market	Qual	Qual_WAVG	Quant	Quant_WAVG
Market		0.88	0.88	1	0.73
Qual	0.12		0.59	0.4	0.13
Qual_WAVG	0.12	0.41		0.27	0.2
Quant	0	0.6	0.73		0.13
Quant_WAVG	0.27	0.87	0.8	0.87	

Tab. 7.15. The results of a pairwise comparison that indicate the percentage of cases (time windows) in which one group (rows) performed better than another one (columns) according to all applied measures based on maximum drawdown (MD), divided into four most numerous regions of a primary investment focus. Source: Author's own study

7.6. Performance in periods of low weak-form informational efficiency of equity markets measured with the use of the relative measures of portfolio performance, as well as raw and excess returns

The results of the first part of the study presented in Chapter 6 indicated that the lowest levels of the market (equity market) informational efficiency mostly occurred in the windows ending in 2008, 2009, and 2020. Mostly, the behaviour of the market efficiency was followed by the efficiency of quantitative and qualitative funds, and therefore, in most cases the lowest levels of the efficiency of funds could be observed in the same windows or in the adjacent ones. In the case of the MDH tests, the lowest levels of the market efficiency could be mostly observed in the window ending in 2009. In the case of the normality tests, the lowest levels of the market efficiency could be observed mostly in the window ending in 2008. The efficiency of the markets systematically decreased up to these windows and then systematically recovered in the following ones. Most likely, this phenomenon was related to the global financial crisis. It would be in line with the studies by Horta et al. (2014), Sensoy and Tabak (2015), Anagnostidis et al. (2016), as well as by Mensi et al. (2017), suggesting that the global financial crisis negatively affected the weak-form informational efficiency of equity markets. Moreover, normality tests revealed another serious decrease in efficiency, which could not be clearly observed in the results of the MDH tests. According to the results of the normality tests, after the post-crisis recovery, the market efficiency decreased again to reach the lowest levels mostly in the window ending in 2020 according to the results obtained for the overall sample. This phenomenon could be connected with coronavirus-related market issues, as proposed in the studies by Dias, Heliodoro, Alexandre, and Silva (2020), Dias et al. (2020), as well as by Lalwani and Meshram (2020), suggesting that the coronavirus outbreak had a negative impact on the weak-form informational efficiency of equity markets. However, according to the results of the normality tests, the market efficiency started to decrease already in the windows preceding the coronavirus outbreak and first news related to the coronavirus. What is even more important, as it was already mentioned, the MDH tests did not clearly confirm the indications of the normality tests. Nevertheless, despite the lack of confirmation from the results of the MDH tests, it was decided to include the window ending in 2020 in the study on the performance of quantitative funds in periods of low weak-form informational efficiency of the markets.

This section verifies the H3 hypothesis, which states that quantitative funds perform better than qualitative funds in periods of low weak-form informational efficiency of equity markets. In order to verify the H3 hypothesis, a comparative analysis of the average performance measures was performed in the windows of the lowest equity market efficiency.

Figures 7.36. - 7.40. present the average results obtained for all performance measures, which were applied in this chapter so far. The results pertain to windows, which indicated by the results of the weak-form informational efficiency study as the windows of the lowest efficiency of equity markets. Windows ending in 2008, 2009, and 2020 constitute windows for which a comparative analysis was performed.

Figure 7.36. presents the average excess and raw returns for each category in the windows indicated by the results of the weak-form informational efficiency study as the windows of the lowest market efficiency. The results pertain to windows ending in 2008, 2009, and 2020. According to Figure 7.36., in the case of the windows ending in 2008 and 2009, on average all fund categories were outperformed by the market. Differences between the fund

categories were not substantial. However, quant funds managed slightly worse compared to qualitative funds. In both fund categories, funds with larger TNA seemed to manage slightly worse. In the case of the window ending in 2020, the results are not so unambiguous. Taking into account excess returns, all fund categories managed to outperform the market. However, in terms of raw returns, only the TNA-weighted fund categories managed to outperform the market. When considering simple average results, both fund types performed similarly. In the case of both measures, larger funds (in terms of TNA managed) managed better than smaller funds. This phenomenon was stronger in the case of quantitative funds.

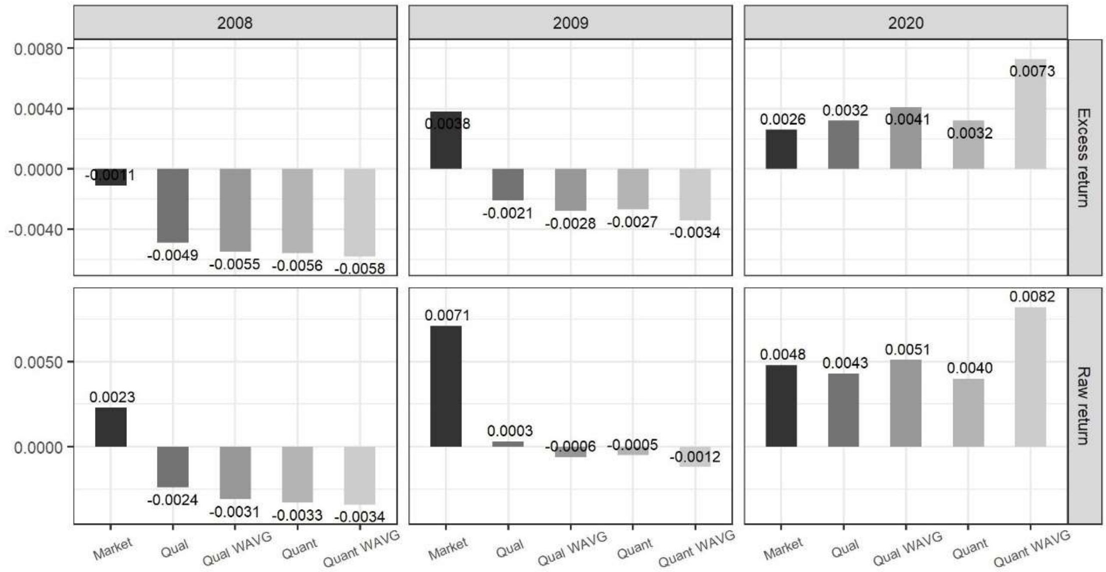

Fig. 7.36. The average monthly raw and excess returns in each time window of the lowest weak-form informational efficiency of equity markets, calculated for the markets (Market), qualitative (Qual), and quantitative (Quant) funds, as well as the average monthly raw and excess returns in the abovementioned time windows weighted by the total net assets of qualitative (Qual WAVG) and quantitative (Quant WAVG) funds. Source: Author's own study

To sum up, in the period related to the global financial crisis, both quant and qual funds were clearly outperformed by the market in terms of excess and raw returns. Quant funds and especially those managing larger TNA performed slightly worse compared to qualitative funds. As opposed to assumptions, the results may suggest that the application of quantitative portfolio management process does not protect portfolio performance against bad effects of informational inefficiency of the markets and does not help to take advantage of opportunities provided by informational inefficiencies as proposed by Parvez and Sudhir (2005). These results allow for making different conclusions compared to the overall results for the entire research period (taking into account all time windows) presented in Figure 7.1. According to the results presented in Figure 7.1., larger quant funds (in terms of TNA managed) performed clearly better compared to smaller quant funds. Additionally, when considering TNA-weighted categories, quantitative funds performed better compared to qualitative funds. Moreover, according to excess returns, the non-weighted fund categories performed just slightly worse compared to the market. Obtained results may suggest that the performance of examined funds suffer in periods of low informational efficiency of equity markets, while in periods of higher efficiency, they make up the losses. It is worth noting that this phenomenon may especially pertain to larger quant funds, which underperform in periods of low efficiency of equity markets and outperform other funds in periods of high efficiency of equity markets. The decrease in the performance of quant funds in periods related to the global financial crisis may also be related to a 'quant meltdown' studied by Khandani and Lo (2011) who proposed that this issue was caused by some errors in the investment strategies of these funds.

Regarding conclusions that can be drawn from the analysis of the results obtained in the window ending in 2020, as opposed to previously discussed windows, fund categories were not substantially outperformed by the market. In fact, when taking into account non-weighted averages, the performance of both types of funds was just slightly different from the performance of the market. Especially larger quant funds in terms of managed TNA seemed to take advantage of opportunities provided by the informational inefficiencies of the market (according to the results of normality). Moreover, the results of all fund categories in the window ending in 2020, were higher compared to the overall results for the entire research period presented in Figure 7.1. The results obtained for the window ending in 2020 were much different from the ones calculated for the windows ending in 2008 and 2009. It also worth noting that as opposed to the windows ending in 2008 and 2009, none of the fund category in the window ending in 2020 had negative values of performance measures.

Moving to the relative measures of portfolio performance, Figure 7.37. presents the average results obtained for the Sharpe and Treynor ratios in the windows of the lowest market efficiency. In the case of the windows ending in 2008 and 2009, the results allow for drawing similar conclusions compared to raw and excess returns. All fund categories were outperformed by the market, whereby in most cases funds managing larger TNA did slightly worse. Again, quant funds managed worse compared to qualitative funds.

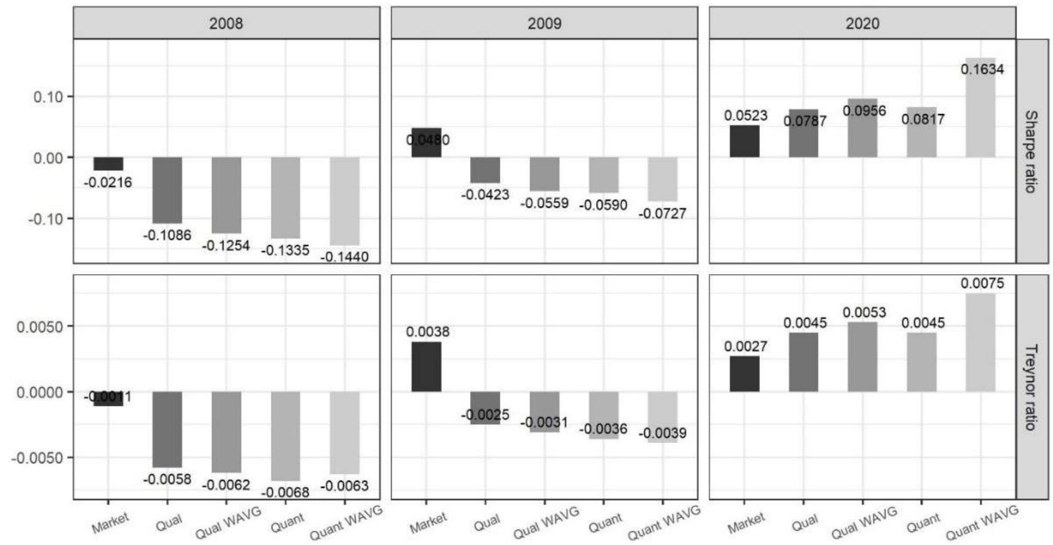

Fig. 7.37. The average Sharpe and Treynor ratios in each time window of the lowest weak-form informational efficiency of equity markets, calculated for the monthly returns of the markets (Market), qualitative (Qual), and quantitative (Quant) funds, as well as the average Sharpe and Treynor ratios calculated for the monthly returns in the abovementioned time windows weighted by the total net assets of qualitative (Qual WAVG) and quantitative (Quant WAVG) funds. Source: Author's own study

The results obtained for the periods of low weak-form informational efficiency of the markets are much different from those calculated for the entire research period (taking into account all time windows) and presented in Figure 7.8. The results suggest that the examined funds suffer especially in periods of low market efficiency, while in periods of higher market efficiency they make up the losses and even gain the advantage over the market. The performance of quantitative funds appears to suffer more in periods of low market efficiency compared to qualitative funds. However, in periods of high market efficiency they appear to perform better compared to qualitative funds. This phenomenon appears to be even stronger when taking into account the TNA-weighted results.

Taking into account the window ending in 2020, this time both Sharpe and Treynor ratios provided average results that allow for drawing unambiguous conclusions. Namely, all fund categories outperformed the market and especially funds with larger TNA managed better (in the case of the raw and excess returns, it was not so clear). When comparing non-weighted fund categories (Quant and Qual), quantitative and qualitative funds performed similarly. However, when comparing TNA-weighted categories (Quant WAVG and Qual WAVG), quantitative funds outperformed qualitative funds significantly. To sum up, funds performed better compared to the market in the window ending in 2020, as opposed to previously discussed windows. In addition, quantitative funds appeared to perform better compared to qualitative funds in the window ending in 2020. It could not be observed in the earlier windows.

Referring to Figure 7.38. presenting the results obtained for the VaR-based measures, Figure 7.39. presenting the results obtained for the LPM-based measures, and Figure 7.40. presenting the results obtained for the MD-based measures, all measures allowed for drawing similar conclusion, also, to those drawn on the basis of the results obtained for the Sharpe and Traynor ratios. A similar situation took place in the analysis of the results for all time windows. The similarity of the indications of different portfolio performance measures obtained in this study validates the findings of Eling and Schuhmacher (2007), Eling (2008), Ornelas, Silva, and Fernandes (2012), as well as Zakamouline (2010).

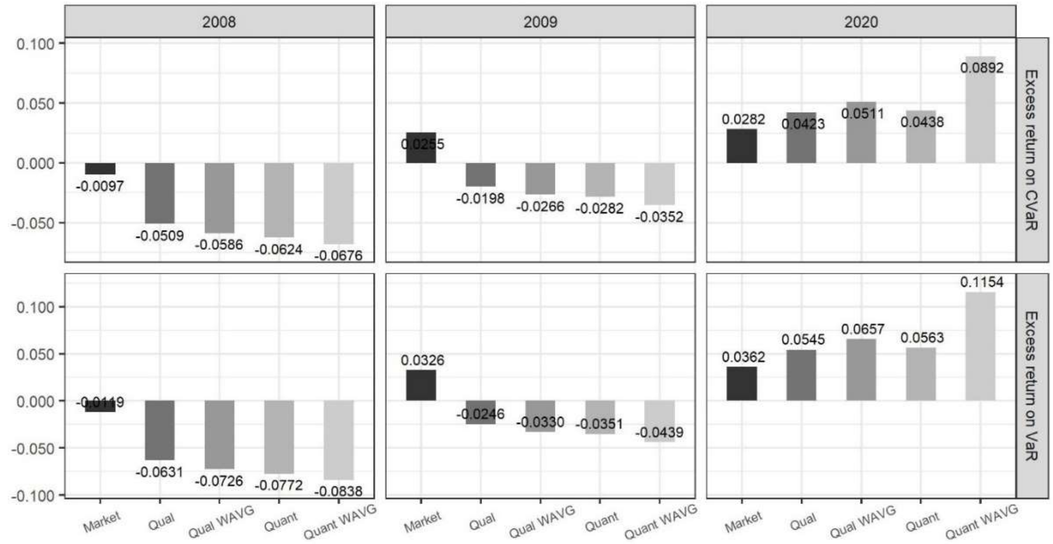

Fig. 7.38. The average excess return on VaR and the average excess return on CVaR in each time window of the lowest weak-form informational efficiency of equity markets, calculated for the monthly returns of the markets (Market), qualitative (Qual), and quantitative (Quant) funds, as well as the average excess return on VaR and the average excess return on CVaR calculated for monthly returns in the abovementioned time windows weighted by the total net assets of qualitative (Qual WAVG) and quantitative (Quant WAVG) funds. Source: Author's own study

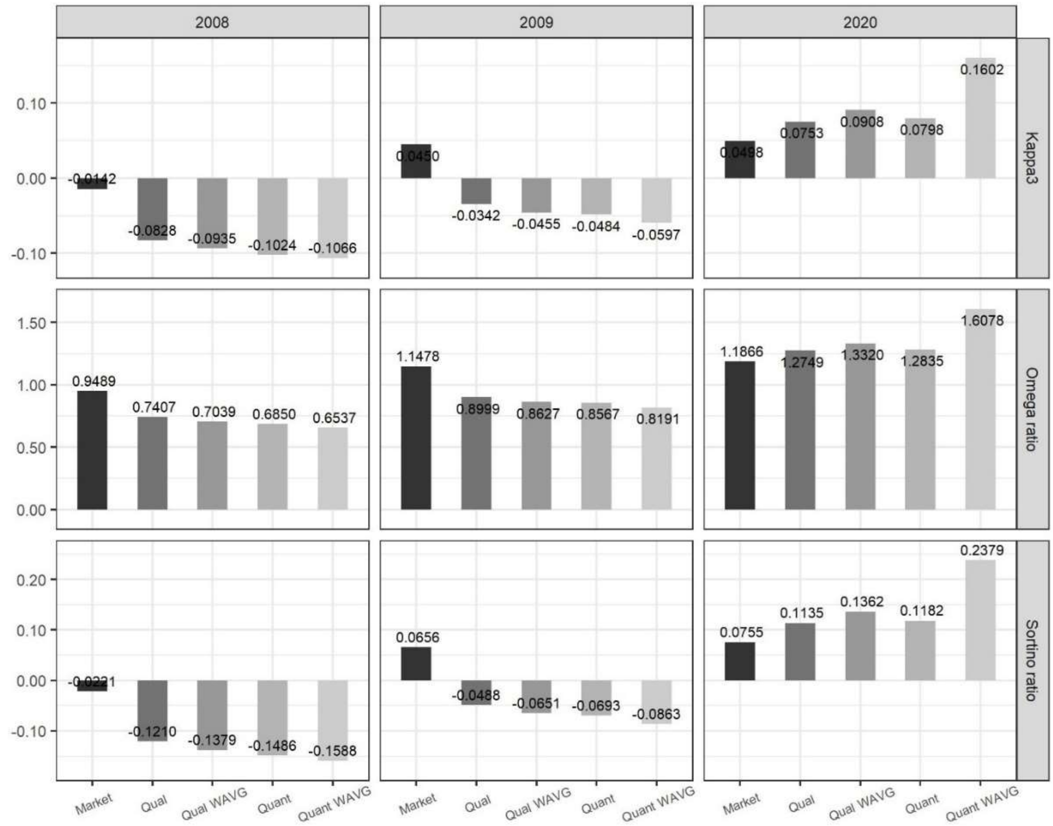

Fig. 7.39. The average Omega, Sortino, and Kappa3 ratios in each time window of the lowest weak-form informational efficiency of equity markets, calculated for the monthly returns of the markets (Market), qualitative (Qual), and quantitative (Quant) funds, as well as the average Omega, Sortino, and Kappa3 ratios calculated for monthly returns in each time window weighted by the total net assets of qualitative (Qual WAVG) and quantitative (Quant WAVG) funds. Source: Author's own study

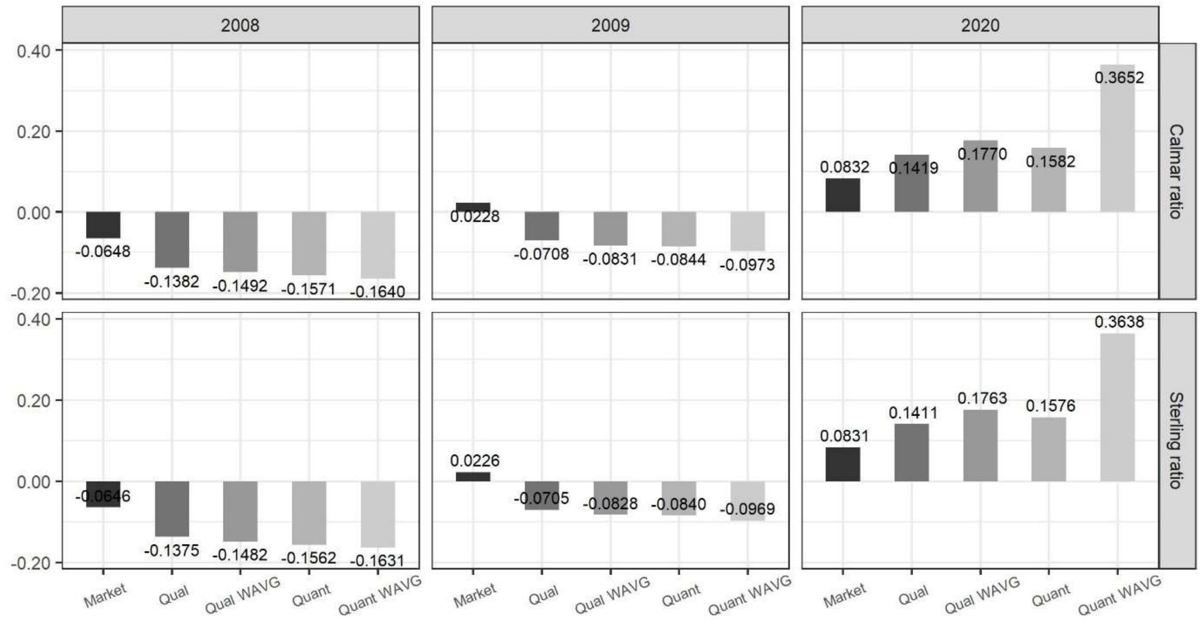

Fig. 7.40. The average Calmar and Sterling ratios in each time window of the lowest weak-form informational efficiency of equity markets, calculated for monthly returns of the markets (Market), qualitative (Qual), and quantitative (Quant) funds, as well as the average Calmar and Sterling ratios calculated for monthly returns in the abovementioned time windows weighted by the total net assets of qualitative (Qual WAVG) and quantitative (Quant WAVG) funds. Source: Author's own study

The contradicting results obtained for the window ending in 2020 in comparison to the results obtained for the windows ending in 2008 and 2009 constitute a very puzzling issue. The results obtained for the windows ending in 2008 and 2009 suggest that the performance of funds examined suffered severely compared to the market. Quant funds and especially the larger ones in terms of TNA managed did worse in these periods compared to qualitative funds. On the other hand, the results received for the window ending in 2020 indicate that funds outperformed the market in period of low informational efficiency. The results obtained for raw returns were an exception. Quant funds and especially the larger ones in terms of TNA managed did better in this period compared to qualitative funds. If the window ending in 2020 really constituted a period of low informational efficiency of equity markets, both quant and qual funds could perform better due to experience gained and lessons learnt from their mistakes made during the global financial crisis. Nevertheless, according to the MDH tests, which are better suited to financial time series, the window ending in 2020 was a standard period in terms of informational efficiency. The performance results in this window also more resemble the average results for the entire research period.

Moving to the examination of performance in different groups of funds distinguished in terms of strategy and the region of a primary investment focus, it was decided to focus on the Sharpe ratio only, as the indications of the results obtained for the other measures were similar. Focusing on just one measure will simplify the comparative analysis of results. Figure 7.41. presents the average results obtained for the Sharpe ratio in the windows of the lowest market efficiency, in selected four different groups of funds distinguished in terms of strategy according to the Lipper Global Classification scheme.

The results obtained for equity and mixed asset funds in the examined windows allow to draw quite similar conclusions to those drawn from the results obtained for the overall sample (see Figure 7.37.). At least when it comes to the comparison of the performance of quantitative and qualitative funds. Much different results can be observed in the case of absolute return an hedge funds. On the one hand, in the window ending in 2020, the results in absolute return and hedge groups allowed to draw similar conclusions to those drawn from to the results obtained for the other groups and the overall sample. On the other hand, in the previous windows (windows ending in 2008 and 2009), the results were much different. Depending on the window (2008/2009) and the group (absolute return/hedge), the performance of quantitative funds was similar to the performance of qualitative funds or was even higher than the performance of qualitative funds. It suggests that in the groups of absolute return and hedge funds, quantitative funds took more advantage from market inefficiencies compared to quantitative funds from the groups of equity and mixed asset funds. In most cases, quantitative funds from absolute return and hedge groups were able to generate even better results than qualitative funds. Only in the groups of absolute return and hedge funds, the average results for quantitative funds were positive.

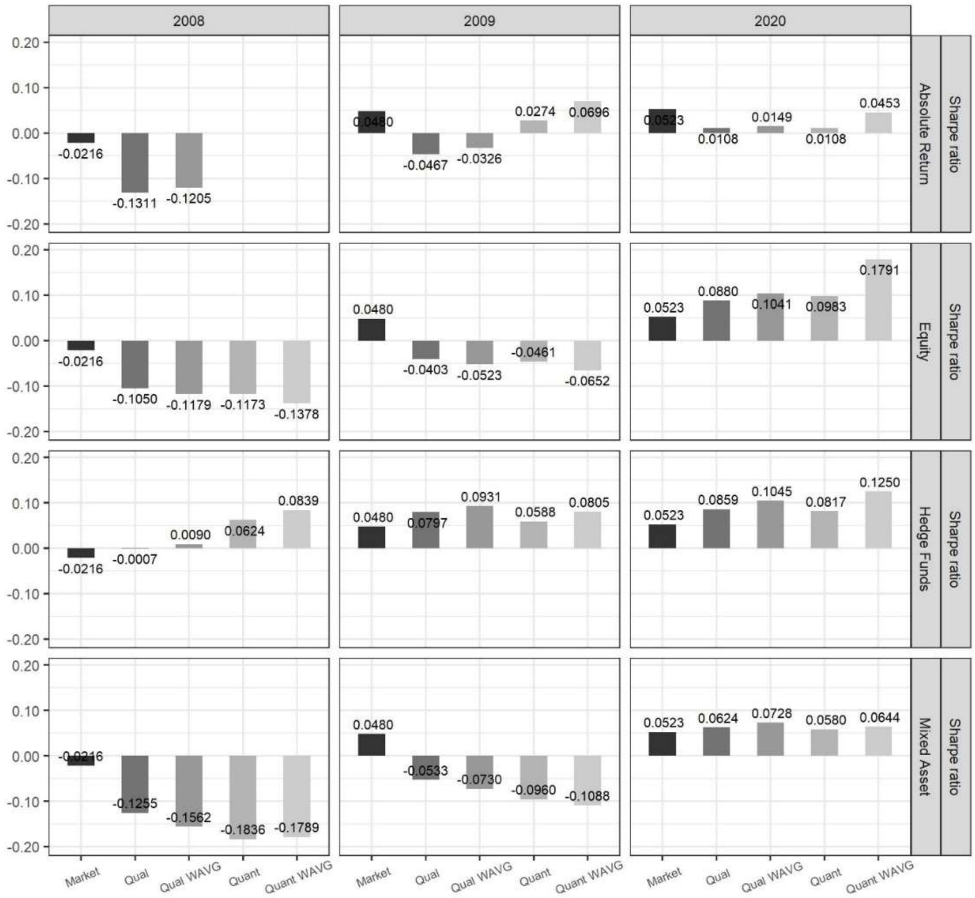

Fig. 7.41. The average Sharpe ratio in each time window of the lowest weak-form informational efficiency of equity markets, calculated for the monthly returns of the markets (Market), qualitative (Qual), and quantitative (Quant) funds, as well as the average Sharpe ratio calculated for monthly returns in the abovementioned time windows weighted by the total net assets of qualitative (Qual WAVG) and quantitative (Quant WAVG) funds, divided into selected four main strategies according to the LGC scheme. Source: Author’s own study

When it comes to the results obtained for four most numerous groups distinguished in terms of the region of the primary investment focus, Figure 7.42. suggests that the results obtained for the groups of funds primarily investing in Eastern Asia, Northern America, and Western Europe allow for drawing conclusions similar to those drawn from the results obtained for the overall sample. At least when it comes to the comparison of the performance of quantitative and qualitative funds. Surprisingly, in the windows ending in 2008 and 2009, in the group of funds primarily investing in Northern Europe, quantitative funds turned out to perform slightly better compared to qualitative funds. Such results are much different from those received for the overall sample and other groups distinguished in terms of the region of a primary investment focus.

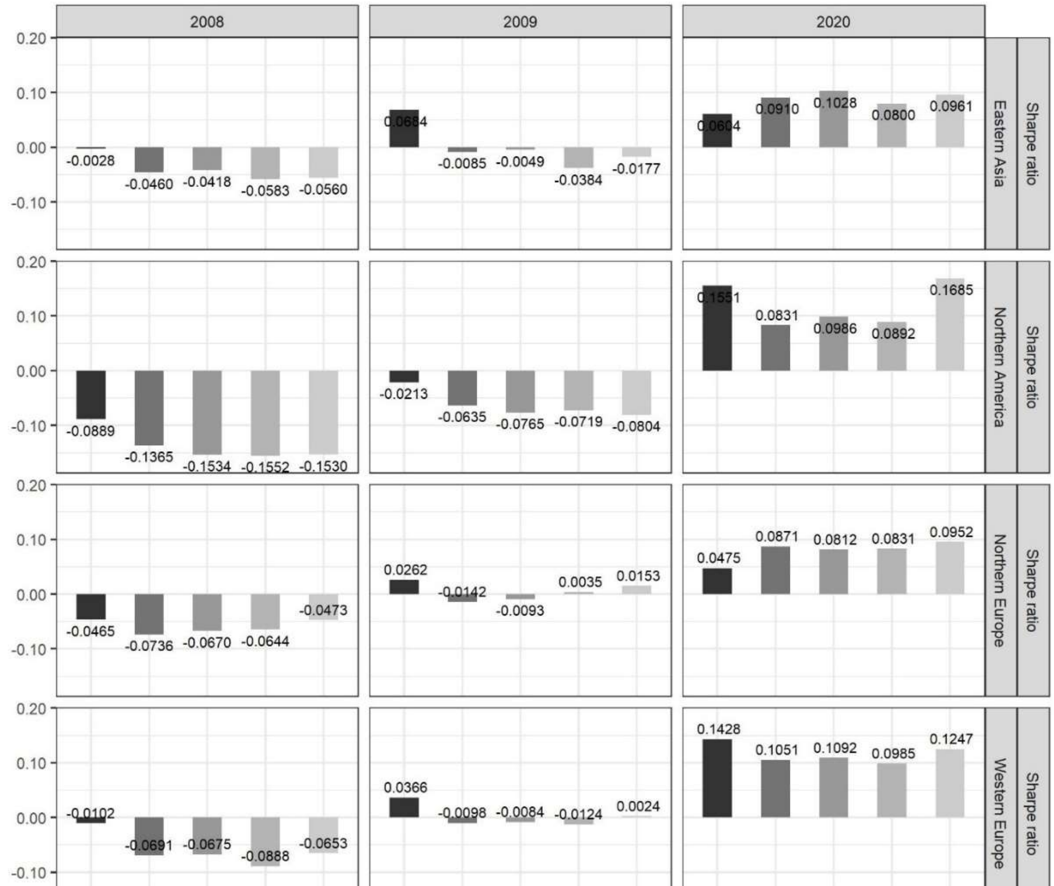

Fig. 7.42. The average Sharpe ratio in each time window of the lowest weak-form informational efficiency of equity markets, calculated for monthly returns of the markets (Market), qualitative (Qual), and quantitative (Quant) funds, as well as the average Sharpe ratio calculated for monthly returns in the abovementioned time windows weighted by the total net assets of qualitative (Qual WAVG) and quantitative (Quant WAVG) funds, divided into four most numerous regions of primary investment focus. Source: Author's own study

7.7. Correlations between the returns of quantitative and qualitative funds

Following Harvey et al. (2017), it was decided to supplement the fund performance study with the study on the Pearson correlation coefficients between the raw returns of quantitative funds and qualitative funds. The analysis of correlations between the raw returns of quantitative and qualitative funds will provide some information on the similarity of raw returns generated by quantitative and qualitative funds. This section aims to answer a supplementary research question of whether quantitative funds are similar to qualitative funds in terms of correlation between their raw returns. The Pearson correlation coefficients were also calculated between selected four main strategies according to the Lipper Global Classification scheme and four most numerous regions of the primary investment focus.

The Pearson correlation coefficients were calculated for monthly raw returns in 60-month windows of the sample selected according to methodology described in Section 5.3.1. i.e., the methodology of the sample selection applied in all calculations in Chapter 6 and Chapter 7. According to this methodology, the correlations were calculated only for time series of funds that met a requirement of at least 90% of a maximum number of observations in a given window (a maximum number of observations was 60). The windows were rolled by 12 months (the next window began 12 months from the beginning of the previous window). The first window began on 01/01/2000 and the last window ended on 31/12/2020.

The Pearson correlation coefficients were calculated between the monthly raw returns of individual funds. The results will be presented as the average Pearson correlation coefficients, which were obtained between quantitative funds only (Quant), qualitative funds only (Qual), as well as between quantitative and qualitative funds together (Quant-Qual), hereinafter referred to as the groups. Due to a large number of correlations and a large usage of computing resources (especially RAM) by the R algorithm computing and summarising results, the calculations were done for smaller sub-samples randomly selected with replacement from a whole research sample. The aforementioned randomly selected sub-samples contained 15% of funds included in the basic research sample. The sub-samples were selected randomly with replacement 30 times and the calculations were made for each of them. Then, in order to obtain the results presented in this section, the results from 30 randomly selected sub-samples were averaged. In the light of limitations related to the usage of computing resources, it was assumed that the aforementioned approach would provide the reliable estimates of the average results of a whole sample.

Moving to the results obtained for the Pearson correlation coefficients, Figure 7.43. presents the average correlation coefficients between monthly raw returns of quantitative funds only (Quant), qualitative funds only (Qual), as well as between quantitative and qualitative funds together (Quant-Qual) in all rolling windows, in the entire research period from 01/01/2000 to 31/12/2020. The results obtained allow for stating that the average correlation coefficients in all groups are positive and moderate. The differences between the groups are slight. The highest average correlation coefficient was obtained for the group of quant funds (0.50). The lowest one was obtained for the group of qualitative funds (0.46). The average correlation coefficient between quant and qual funds amounts to 0.47. To sum up, the strategies applied by quantitative and qualitative funds seem to be moderately similar in terms of raw returns they generate. It is worth stressing that in this respect, quantitative funds are slightly more similar to each other than qualitative funds.

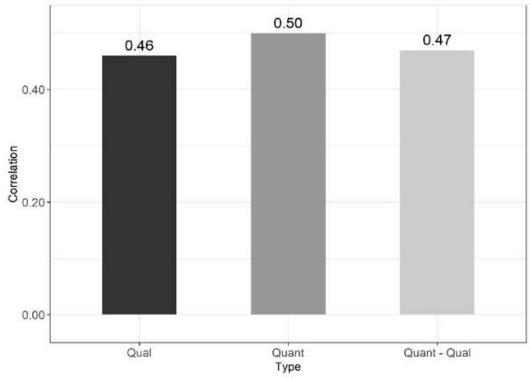

Fig. 7.43. The average correlation coefficients (the average Pearson correlation coefficients) between the monthly raw returns of quantitative funds only (Quant), qualitative funds only (Qual), as well as between quantitative and qualitative funds together (Quant-Qual) in all rolling windows, in the entire research period from 01/01/2000 to 31/12/2020. Source: Author's own study

According to Figure 7.44., which shows how the average Pearson correlation coefficients behaved over the windows, the correlation coefficients in the group of quantitative funds were mostly higher over the windows compared to other two groups. The average correlation coefficients in the group of qualitative funds were mostly the lowest among the groups. Figure 7.44. clearly shows that the levels of the average correlation coefficients changed substantially over the windows, from being on the verge of positively low and moderate to positively high. The behaviour of the correlation coefficients was similar in all three groups examined. The correlation coefficients substantially fell from the window ending in 2005 to the window ending in 2007. In the following windows, the correlation coefficients recovered up to the window ending in 2011, where their values indicated high positive correlations in all groups. In the following windows, the correlation coefficients decreased systematically up to the window ending in 2018, where their values were the lowest and indicated positively low/moderate correlations in all groups. In the following windows, the correlation coefficients recovered to moderate levels. According to the results obtained, quantitative and qualitative funds appear to apply similar strategies in terms of raw returns they generate.

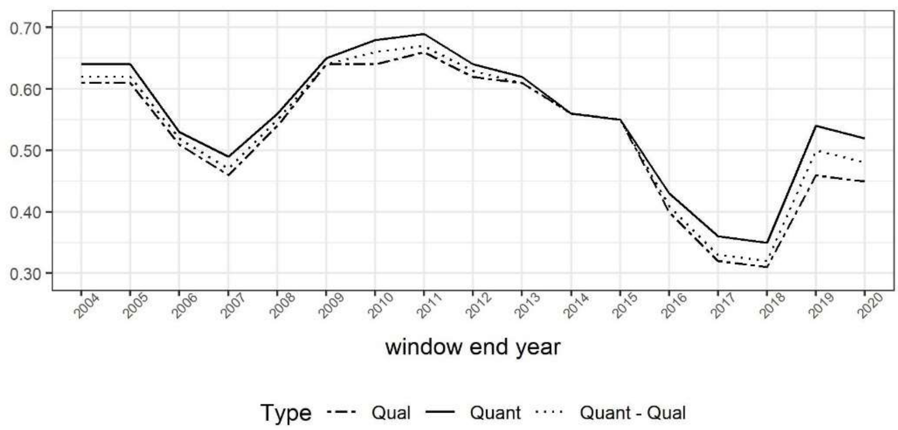

Fig. 7.44. The average correlation coefficients (average Pearson correlation coefficients) between the monthly raw returns of quantitative funds only (Quant), qualitative funds only (Qual), as well as between quantitative and qualitative funds together (Quant-Qual) in each time window, in the research period from 01/01/2000 to 31/12/2020. Source: Author's own study

Figure 7.45. similarly to Figure 7.43. presents the average correlation coefficients between monthly raw returns of quantitative funds only (Quant), qualitative funds only (Qual), as well as between quantitative and qualitative funds together (Quant-Qual) in all rolling windows, in the entire research period from 01/01/2000 to 31/12/2020. Nevertheless, this time, the correlations are also between and within selected four main strategies according to the Lipper Global Classification scheme. The results presented in Figure 7.45. allow for drawing several major conclusions. One of them is that correlations are strategy-dependent. The lowest results indicating low and positive correlations can be observed in the groups of funds related to hedge funds. Only in these groups, the average correlation coefficients of quant funds are lower compared to the average correlation coefficients of qualitative funds solely, as well as quantitative and qualitative funds together. It suggests that especially quant hedge funds apply varied strategies in terms of raw returns they generate. Slightly higher correlations can be observed in the groups related to absolute return funds. However, they can be considered on the verge of low and moderate correlations. The highest correlations can be observed in the groups related to equity and mixed asset funds solely and together. Correlations in these groups can certainly be considered moderate. In these groups, funds apply most similar strategies in terms of raw returns they generate. A common feature of the groups examined is that the differences between correlations of quant funds solely, qual funds solely, as well as quant and qual funds together are mostly slight. Low correlations in the groups related to hedge and absolute return funds (especially compared to equity and mixed asset funds) seem to be justified, as funds from these groups are expected to apply varied and sophisticated strategies engaging derivatives and short positions.

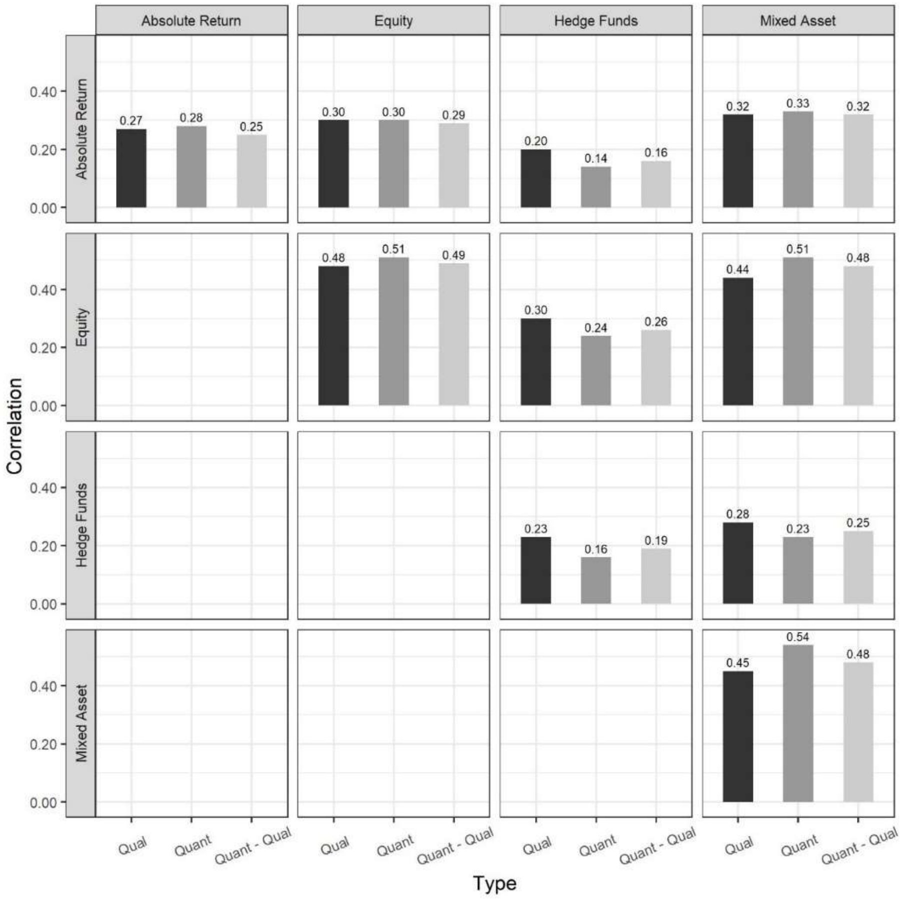

Fig. 7.45. The average correlation coefficients (average Pearson correlation coefficients) between the monthly raw returns of quantitative funds only (Quant), qualitative funds only (Qual), as well as between quantitative and qualitative funds together (Quant-Qual) between and within selected four main strategies according to the LGC scheme in all rolling windows, in the entire research period from 01/01/2000 to 31/12/2020. Source: Author's own study

Figure 7.46. systematizes the results in a similar way to Figure 7.45. However, this time, the correlations are between and within four most numerous regions of the primary investment focus. According to the results presented in Figure 7.46., the correlations are region-dependent. The lowest average correlations can be observed in the groups related to funds primarily investing in the region of Eastern Asia. The highest correlations on the verge of moderate and high can be observed in the case of the groups of funds primarily investing in Northern America (solely), Northern Europe (solely), and Western Europe (solely). However, in the case of Northern America and Western Europe, the correlations were slightly lower compared to Northern Europe. Differences between correlations among the quant funds solely, qual funds solely, as well as quant and qual funds together are slight. In just two out of ten examined groups, which were presented in Figure 7.46., the average correlation coefficients for quantitative funds (solely) were higher than the average correlation coefficients for qualitative funds (solely).

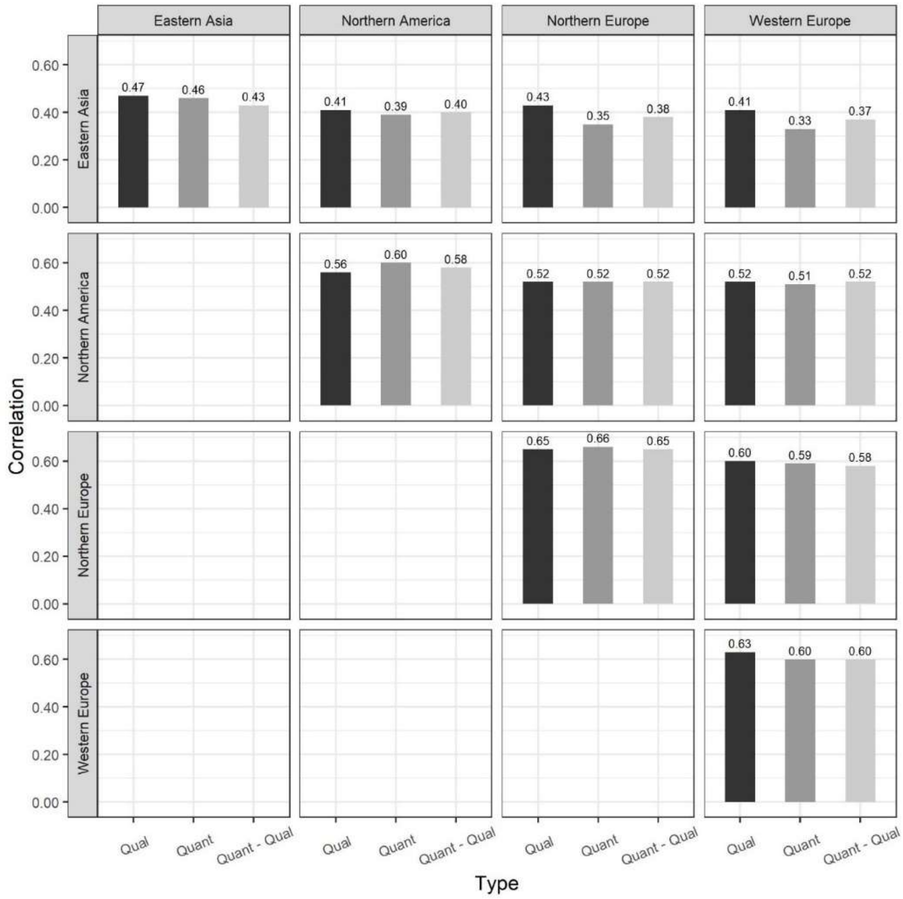

Fig. 7.46. The average correlation coefficients (average Pearson correlation coefficients) between the monthly raw returns of quantitative funds only (Quant), qualitative funds only (Qual), as well as between quantitative and qualitative funds together (Quant-Qual) between and within four most numerous regions of the primary investment focus in all rolling windows, in the entire research period from 01/01/2000 to 31/12/2020. Source: Author's own study

7.8. Conclusions

Considering the overall sample that included all strategies and regions, according to the average results for the entire research period, which were obtained for the relative measures of portfolio performance, quantitative funds outperformed qualitative funds and the market. Quant funds performed even better than qualitative funds when considering the TNA-weighted average results. It may also suggest that larger quantitative funds performed better than smaller quantitative funds. These conclusions were also confirmed by slightly more frequent outperformance of the market and qualitative funds by quantitative funds when considering the average results for particular windows. Nevertheless, the advantage of quantitative funds was not substantially systematic. The results obtained for the overall sample allow for stating that the application of quantitative portfolio management processes may increase performance and help gain advantage over traditional portfolio management styles.

The results obtained for the overall sample, however, this time for raw and excess returns, allowed for drawing quite different conclusions compared to the relative measures of portfolio performance. Namely, both traditional and quantitative portfolio management processes did not provide any better average performance compared to the market. The market outperformed both approaches to portfolio management in the majority of cases. What is more, according to unadjusted returns and the non-weighted average results, quantitative funds were outperformed by qualitative funds in the majority of cases. Such differences in the results obtained for raw returns, excess returns, and the relative measure of portfolio performance may suggest that quantitative funds generate much less risk in terms of the distribution of their returns compared to qualitative funds and the equity market. It is worth noting that when considering the TNA-weighted average results, quantitative funds appeared to outperform qualitative funds in the majority of cases. This result may suggest that, especially larger quantitative funds, have the ability to outperform qualitative funds.

When it comes to the results at the level of particular strategies, they mostly differed from the results obtained for the overall sample. Differences between quantitative and qualitative funds appeared to be different in the groups examined. According to relative measures of portfolio performance, quantitative funds outperformed qualitative funds in the majority of cases in the groups of absolute return and equity funds. However, only in the case of the group of absolute return funds, quantitative funds had a clearly systematic advantage over qualitative funds. The opposite could be observed in the case of mixed asset funds. When considering the results obtained for raw and excess returns, only in the case of absolute return funds, quantitative funds had a clear advantage over qualitative funds. In the groups of equity and hedge funds, quantitative funds outperformed qualitative funds in the majority of cases according to the TNA-weighted average results only.

At the level of particular regions, according to the relative measures of portfolio performance, in the majority of cases, quantitative funds were outperformed by qualitative funds in terms of the non-weighted average results. The situation appeared to be quite different when considering the TNA-weighted results. After accounting for TNA, quantitative funds turned out to outperform qualitative funds in the majority of cases in the groups of funds primarily investing in Northern America, Northern Europe, and Western Europe. The differences between quantitative and qualitative funds appeared to be different in the groups examined.

The main research hypothesis H1 states that the performance of quantitative funds is higher than the performance of qualitative funds. The results obtained in the second part of the study do not unambiguously suggest rejecting the H1 hypothesis. There were groups in which quantitative funds had the advantage over qualitative funds. However, they were in the minority. What is more, only in the group of absolute return funds, quantitative funds clearly outperformed qualitative funds.

Regarding the differences in performance between quantitative funds and their relevant equity market benchmarks, when looking at the results obtained for the relative measures of portfolio performance in the second part of the study, quantitative funds turned out to clearly systematically outperform the market only in the case of hedge funds. Moreover, the outperformance of the market by quantitative funds, but not that systematic, could be observed in the case of a whole sample, samples of absolute return and equity funds, as well as sample of funds primarily investing in Eastern Asia. On the other hand, the market systematically outperformed quantitative funds in the case of funds primarily investing in the remaining three regions. A not so clear outperformance of quantitative funds by the market could be observed in the group of mixed asset funds. The abovementioned considerations pertained to the indications of the relative measures of portfolio performance. According to raw and excess returns, quantitative funds were dominated by the market across almost all analysed groups. It suggests that the risk related to investment in quantitative funds is much lower compared to investment in a passive equity market portfolio.

The second part of the study delivered some interesting conclusions pertaining to the relationship between the size of quantitative funds and their performance. The results obtained suggest that larger quantitative funds in terms of TNA delivered higher performance than smaller quantitative funds in the majority of cases across almost all analysed groups. The larger funds in terms of TNA delivered higher performance also in the group of qualitative funds. However, it did not pertain to such many examined samples as in the case of quantitative funds. The outperformance of smaller funds by larger ones was not so clear. In the case of some groups distinguished in terms of the region of the primary investment focus, larger qualitative funds managed even worse. Such groups were qualitative funds primarily investing in Northern America, Northern Europe, and Western Europe. A higher positive relation between TNA and performance in the case of quantitative funds may suggest that TNA managed have a greater impact on performance in the case of quantitative funds. Larger managed funds may be related to larger expenditures on development of profitable strategies.

Regarding the homogeneity of results obtained for quantitative and qualitative funds, the interquartile range of quantitative funds was slightly higher compared to qualitative funds in the case of the majority of relative measures of portfolio performance. The spread was examined only for the overall sample. In the case of raw and excess returns, almost no differences in spread could be observed. The main differences in spreads between quantitative and qualitative funds appeared to result from the differences in the 75th percentiles. The 75th percentiles were higher in the case of quantitative funds, suggesting that the upper 25% of observations of the relative measures of portfolio performance in the quant fund group had higher values.

The following supplementary research question pertained to the similarity of quantitative and qualitative funds in terms of the correlation between their raw returns. When considering the results obtained for the entire research sample and all windows, the average Pearson correlation coefficients in the groups of quantitative and qualitative funds appeared to be positive, moderate, and quite similar. In the case of quantitative funds, the average Pearson correlation coefficient was just slightly higher, suggesting that quantitative funds were slightly more similar to each other than qualitative funds in terms of the correlation between their raw returns. The average correlation coefficient between quantitative and qualitative funds was very similar to the abovementioned coefficients. The levels of the Pearson correlation coefficient in the examined groups changed substantially over the windows, from being on the verge of positively low and moderate to positively high. The behaviour of the correlation coefficients was similar in the groups of quantitative and qualitative funds.

When taking into account the results obtained between and within the strategies, the results turned out to be strategy-dependent. The lowest results indicating low and positive correlations could be observed in the groups paired with hedge funds. Only in these groups, the average correlation coefficients of quant funds were lower compared to qualitative funds. Slightly higher correlations could be observed in the groups paired with absolute return funds. The highest correlations could be observed in the groups related to equity and mixed asset funds. Correlations in these groups could be considered moderate. In these groups, funds applied the most similar strategies in terms of the raw returns generated. A common feature of the groups examined was that the differences between the correlations of quant and qual funds were mostly slight. Low correlations in the groups related to hedge and absolute return funds seem to be justified, as funds from these groups are expected to apply varied and sophisticated strategies engaging derivatives and short positions.

In the case of the grouping by the region of a primary investment focus, the correlations turned out to be region-dependent. The lowest average correlation coefficients could be observed in the groups paired with the groups of funds primarily investing in the region of Eastern Asia. The highest correlations on the verge of moderate and high could be observed in the case of the group of funds primarily investing in Northern Europe. Slightly lower correlations could be observed in the groups of Northern America and Western Europe. Differences between the correlations among the quant and qual funds were slight.

When it comes to the study on the performance of quantitative funds in periods of low weak-form informational efficiency of equity market, the results provided for the overall sample by the applied performance measures allow to make consistent conclusions, namely, in period related to the global financial crisis, quantitative funds (especially the larger ones in terms of TNA managed) performed slightly worse compared to qualitative funds and significantly worse compared to the market. It suggests that, as opposed to the assumptions proposed in the study by Parvez and Sudhir (2005), the application of quantitative portfolio management process does not protect the portfolio performance against the bad effects of informational inefficiency of the markets and does not help to take advantage of the opportunities provided by informational inefficiencies. Quite different results were mostly obtained for the window ending in 2020. If the window ending in 2020 really constituted the period of low informational efficiency of the markets, both quant and qual funds could perform better due to experience gained and lessons learnt from their mistakes made during the global financial crisis. Nevertheless, the results obtained for this window should be approached with caution, as according to more reliable MDH tests, which are better suited to financial time series, the window ending in 2020 should not be considered the period of low informational efficiency at all.

Not all groups of funds distinguished in terms of the applied strategy provided results similar to results of the overall sample in periods of low weak-form informational efficiency of the equity market. In the case of absolute return and hedge funds, in the windows related to the global financial crisis, quantitative funds were able to generate similar or higher performance compared to qualitative funds. The results obtained for the other two groups allowed for drawing similar conclusions as in the case of the overall sample. Also, in the case of groups distinguished in terms of the region of the primary investment focus, there was a group that provided results, which were different from those for the overall sample. In the case of funds primarily investing in Northern Europe, in the windows related to the global financial crisis, quantitative funds were able to generate higher performance compared to qualitative funds.

A supplementary research hypothesis H3 states that quantitative funds perform better than qualitative funds in periods of low weak-form informational efficiency of equity markets. The results obtained in the second part of the study do not unambiguously suggest rejecting the H3 hypothesis. There were groups in which quantitative funds had the advantage over qualitative funds in periods of low weak-form informational efficiency of equity markets. However, they were in the minority.

It is also worth adding that the results obtained for the relative measures of portfolio performance were in line with the findings of Eling and Schuhmacher (2007), Eling (2008), Ornelas, Silva, and Fernandes (2012), as well as Zakamouline (2010), who proposed that different relative measures of portfolio performance allow for developing similar rankings. In this study, typical rankings at the level of individual funds were not developed. Nevertheless, different relative measures of portfolio performance enabled making similar conclusions regarding the performance of quantitative funds in comparison to the performance of qualitative funds and their relevant equity markets. When it comes to the results obtained for raw and excess returns, certainly, in most cases, they did not allow for making similar conclusions to those made on the basis of the results obtained for the relative measures of portfolio performance. In the case of some of the examined samples, accounting for risk seriously affected conclusions pertaining to differences in performance between quantitative and qualitative funds, as well as their relevant equity market benchmarks.

8. The results of the study on the performance of quantitative funds with the use of econometric models - the third part of the study

This chapter discusses the results of the third part of the study, i.e., the one referring to the performance of quantitative funds with the use of two econometric models, which are commonly applied in the issue-related studies, namely the Capital Asset Pricing Model (CAPM) and the Treynor-Mazuy model (TM). The classic versions of the these models have been modified in order to achieve the objectives of this study. Additionally, this chapter presents the final research sample that was used in the third part of the study, as it differs from the final sample applied in the first and second part of the study.

The main research objective of the third part of the study is to answer the question of whether the performance of quantitative funds is higher than the performance of qualitative funds. What is more, the third part of the study also aims to answer the question of whether quantitative funds perform better than qualitative funds in periods of low weak-form informational efficiency of equity markets.

The rolling window method was also used in the third part of the study. However, the parameters of this method were changed. This resulted in a different final research sample compared to the first and the second part of the study. The final research sample applied in the third part of the study is presented in Section 8.1. Section 8.1. also presents and discusses the results of the estimations of the modified Capital Asset Pricing Model (CAPM). Section 8.2. presents and discusses the results of the estimations of the modified Treynor-Mazuy model (TM). Section 8.3. presents and discusses the results of the study on the performance of quantitative funds in periods of low weak-form efficiency of equity markets.

8.1. The Capital Asset Pricing Model (CAPM)

Table 8.1. presents the number and the percentage share of unique quantitative funds and qualitative funds in the entire research period from 01/01/2000 to 31/12/2020, which were qualified to the third part of the study, as they met the requirement of at least 80% of monthly observations in a 84-month window, in at least one window. The number of unique funds presented in Table 8.1. shows that quantitative funds constitute just a fraction of a whole research sample. Quantitative funds constituted around 4.5% in the number of unique funds. The final research sample of the third part of the study consisted of 78 472 unique qualitative funds and 3 670 unique quantitative funds. The percentage shares of quantitative and qualitative funds in the final research sample of the third part of the study did not change much compared to the final research sample of the first and second parts of the study.

Fund type	Unique funds	Percentage
Qualitative	78472	95.53%
Quantitative	3670	4.47%
Total	82142	100.00%

Tab. 8.1. The number of unique quantitative and qualitative funds, as well as their percentage share in the entire research period from 01/01/2000 to 31/12/2020. Source: Author's own study

The modified CAPM model (already discussed in Section 5.3.3.) can be described by the equation:

$$R_{it} - Rf_t = \alpha + \beta_1(Rm_t - Rf_t) + \beta_2 Type_i + \beta_3 Type_i(Rm_t - Rf_t) + \varepsilon \qquad (5.1.)$$

where:
R_{it} – the logarithmic monthly returns of fund i in time t,
Rf_t – the yield of the adequate risk-free rate in time t,
Rm_t – the logarithmic monthly returns of the adequate stock market index in time t,
$Type_i$– dummy variable that takes the value of 0 for qualitative fund and the value of 1 for quantitative fund.

The model was estimated for the overall sample (the final research sample including all funds examined), separately for each of four groups of funds distinguished in terms of the main strategy according to the Lipper Global Classification scheme and separately for each of four largest groups of funds distinguished in terms of the geographic region of a primary investment focus.

Overall results

The modified CAPM model was estimated using a pooled OLS regression. Random effects and fixed effects models were also considered; however, the results of the Breusch and Pagan Lagrange multiplier test for random effects and the F test for no fixed effects indicated that random effects and fixed effects models would be applicable only in the case of 5 out of 15 windows (33.33% of windows). Thus, it was decided to apply a pooled OLS regression. Nevertheless, in the case of the overall sample, the results of both a pooled OLS regression and fixed effects model will be presented in order to check if the models provide similar estimates. Standard errors in the pooled OLS regression were corrected using the Newey-West procedure with automatic lag selection.

Figure 8.1. presents R-squared, adjusted R-squared, and the p-value of the F-test of the modified CAPM model estimated in each 84-month rolling window for the overall sample. In the case of plots for R-squared and adjusted R-squared, a red dashed line signifies a value of 0. In the case of the plot for the p-value of the F-test, a red dashed line signifies a significance level of 0.05. Referring to the R-squared and the adjusted R-squared presented in Figure 8.1., the models seem to be fitted to actual data rather weakly. At the same time, the R-squared and

the adjusted R-squared of the fixed effects model and pooled regression were very similar over time windows. It is not easy to spot any long-term trends in the behaviour of goodness-of-fit measures, which have been applied in this study. Nevertheless, they seem to fall in the long term starting from the window ending in 2009 up to the window ending in 2018. In earlier and subsequent windows, the goodness of fit of the estimated CAPM models to actual data seemed to rise.

The R-squared of a fixed effects model ranged from 20.85% to 35.31% with an average result of 27.94%. In the case of a pooled OLS regression, the R-squared ranged from 20.80% to 35.06% with an average result of 27.83%. The adjusted R-squared of a fixed effects model ranged from 19.77% to 34.39% with an average result of 26.93%. In the case of a pooled OLS regression, the adjusted R-squared ranged from 20.80% to 35.06% with an average result of 27.83%. The results obtained indicate that both models provide a very similar goodness of fit. When it comes to the p-value of the F-test, the results obtained indicate that the fixed effects model, as well as the pooled regression, provide a better fit than the intercept-only model.

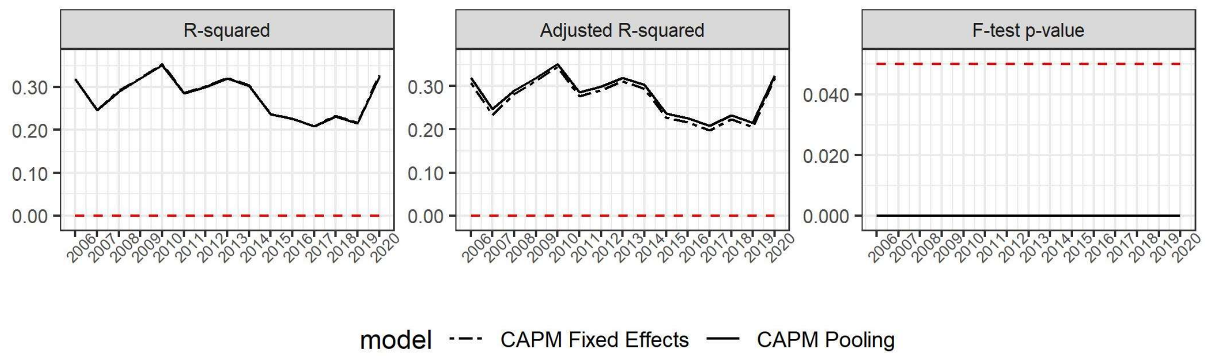

Fig. 8.1. R-squared, adjusted R-squared, and the p-value of the F-test of the modified CAPM model estimated in each 84-month rolling window for the overall sample with the use of a pooled OLS regression and fixed effects model. Source: Author's own study

Moving to estimated coefficients of the modified CAPM model, Figure 8.2. presents parameters and their p-values, estimated in each 84-month rolling window for the overall sample with the use of a pooled OLS regression and fixed effects model. The red dashed lines in the plots with coefficients (first row) signify the 0 value. The red dashed lines in the plots with the p-values of the estimated coefficients (second row) refer to the 0.05 significance level.

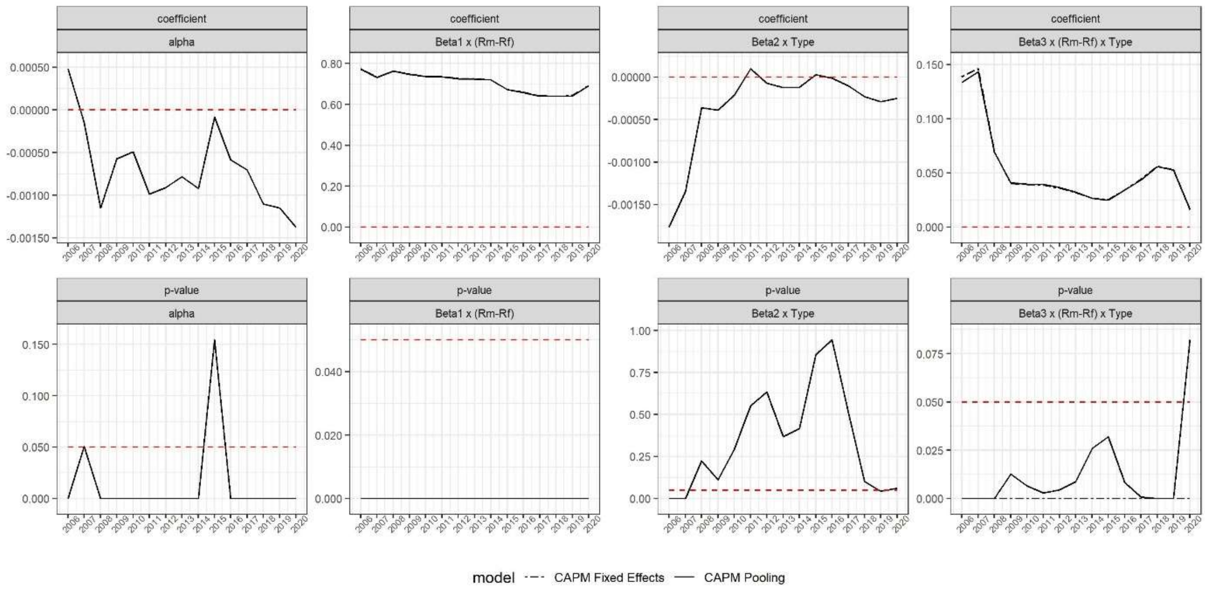

Fig. 8.2. Parameters and the p-values of the parameters of the modified CAPM model, estimated in each 84-month rolling window for the overall sample with the use of a pooled OLS regression and fixed effects model. Source: Author's own study

Only Beta1 (β_1) and Beta3 (β_3) coefficients have been estimated in the fixed effect model due to its nature. Referring to Figure 8.2., the estimates of the Beta1 (β_1) and Beta3 (β_3) coefficients are very similar in both the pooled OLS regression and the fixed effect model.

The alpha (α) coefficient also known as Jensen's alpha was negative and statistically significant in almost all windows, suggesting that the examined funds systematically generated worse performance than the market. The results of funds were lower that the results of a passive investment in the equity market portfolio. It is worth noting that starting from the window ending in 2015, the alfa (α) systematically decreased. It indicates that performance of quantitative and qualitative funds together was getting worse compared to the market.

The Beta1 (β_1) coefficient was statistically significant in all windows and its value ranged from about 0.64 to about 0.78, which means that all analysed funds were less volatile than the equity market. The increase (decrease) of market risk premium that was equal to one percentage point resulted in the increase (decrease) of risk premium of examined funds that was equal to less than one percentage point. Figure 8.2. also suggests that Beta1 (β_1) was in a downward trend, which means that a systematic risk of funds systematically fell. When considering the final research sample containing four different groups of funds distinguished in terms of strategy applied, it is difficult to conclude if this systematic decrease in dependence on the market was an intentional action of portfolio managers. This phenomenon is likely related to a decreasing share of equity funds, which appear to be the most market-dependent. These doubts should be resolved in the upcoming analysis of results for separate strategies.

Beta2 (β_2) is negative in almost all windows but also statistically insignificant, which means that the type of a fund, i.e., whether it is qualitative or quantitative, may have no impact on alpha (α). In other words, there are no statistically significant differences between quantitative and qualitative funds when it comes to generated alpha (α).

Unlike Beta2 (β_2), the Beta3 (β_3) coefficient was positive and statistically significant in almost all windows. However, it was in a downward trend, falling from about 0.13 in the window ending in 2006 (first window) to about 0.02 in the window ending in 2020 (the last window), which means that it was important whether a fund was qualitative or quantitative in terms of a systematic risk. Quant funds had higher systematic risk. However, it was systematically decreasing over the windows. It may suggest that quantitative funds systematically decreased their dependence on the equity market conditions.

Results by strategy

In order to answer a supplementary research question of whether differences in performance between quantitative and qualitative funds differ between the groups of funds distinguished in terms of strategy, the following part of this section discusses the results of the estimation of the modified CAPM model for different strategies separately. Figure 8.3. presents the R-squared, the adjusted R-squared and the p-value of the F-test of the modified CAPM model estimated in each 84-month rolling window for each strategy separately with the use of a pooled OLS regression. Referring to Figure 8.3., the highest R-squared out of all examined strategies features equity funds, which is most likely due to their highest dependency on the stock market. The R-squared of equity funds ranges from about 27.34% to 42.66% with a mean value of 33.97% and exhibits a long-term sideways trend. Despite the fact that equity funds are marked by the highest R-squared, the fit of their estimated model to actual data can be rather considered weak. The goodness of fit of the models of other strategies is only weaker.

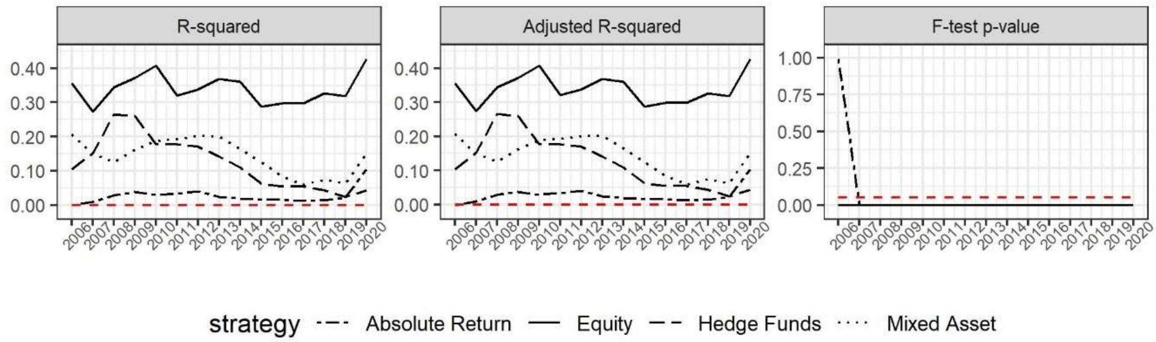

Fig. 8.3. R-squared, adjusted R-squared, and the p-value of the F-test of the modified CAPM model estimated in each 84-month rolling window for each strategy separately with the use of a pooled OLS regression. Source: Author's own study

Hedge funds and mixed asset funds are marked by a lower R-squared compared to equity funds. This is most likely due to their lower connection to the equity markets compared to equity funds. The R-squared of both groups seems to decrease in the long term; however, in the last window it increased significantly. The increase in the last window also pertains to other groups. The R-squared of hedge funds ranges from about 2.41% to 26.57% with a mean value of 12.28%. The R-squared of mixed asset funds ranges from about 5.98% to 20.69% with a mean value of 14.32%. The lowest R-squared features absolute return funds. It may be explained by the nature of absolute return funds, as their strategy aims to generate returns independently from the market. The R-squared of absolute return funds ranges from about 0.01% to 10.43% with a mean value of 2.70%. The values of the adjusted R-squared are very similar to the values of the R-squared. The p-values of the F-tests indicate that, in the majority of cases, the models provide a better fit than the intercept-only model.

Figure 8.4. presents the parameters of the modified CAPM model and their p-values, estimated in each 84-month rolling window for each strategy separately with the use of a pooled OLS regression. Referring to Figure 8.4., only in the case of hedge funds, the alpha (α) parameter was positive in the majority of windows. However, it was regularly decreasing to finally be negative. Although it finally turned negative in the last few windows, it was still higher compared to the other three groups. The results obtained suggest that only hedge funds managed to outperform the market in most cases. Nevertheless, their advantage regularly diminished, suggesting that their performance was getting worse.

In the case of the other strategies, the alpha (α) was mostly negative. The values of alpha (α) in the remaining three groups did not differ much and were marked by a long-term sideways trend. Such results suggest that portfolio managers of equity, absolute return, and mixed asset funds systematically generated worse performance compared to a passive investment in equity market.

In the group of absolute return funds, the alpha (α) was statistically significant in 40% of windows that made up the lowest rate of statistically significant alphas (α) among four strategies. In the group of equity funds, all alphas (α) were statistically significant. In the group of mixed asset funds, 86.67% of the alphas (α) were statistically significant, while in the group of hedge funds, this rate reached 60.00%. The p-values of the estimated alphas (α) suggest that the aforementioned conclusions hold, especially in the case of equity and mixed asset funds.

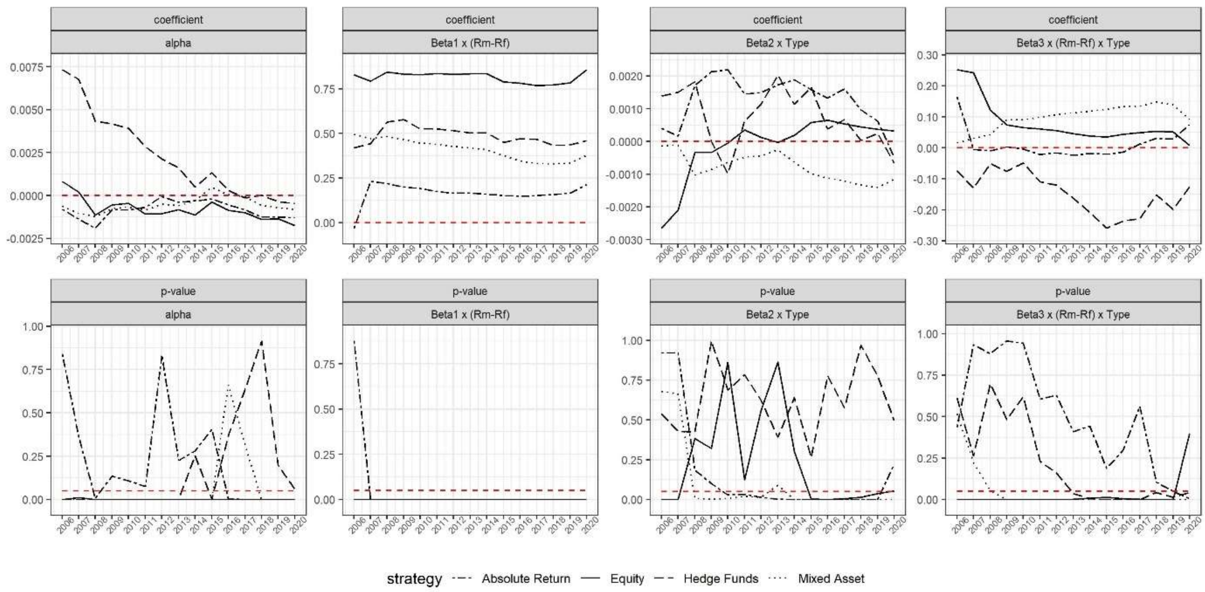

Fig. 8.4. Parameters and the p-values of the parameters of the modified CAPM model, estimated in each 84-month rolling window for each strategy separately with the use of a pooled OLS regression. Source: Author's own study

Moving to Beta1 (β_1), the highest values of this coefficient feature equity funds (the highest systematic risk and equity market dependency). Hedge funds tended to have second largest Beta1 (β_1) values. Third in line in terms of the Beta1 (β_1) values were mixed asset funds. The lowest values of the systematic risk measure featured absolute return funds. Almost all Beta1 (β_1) values were statistically significant, which allows for stating that the aforementioned conclusions were valid.

In the case of all strategies, the values of the estimated Beta1 (β_1) coefficients suggest that the fund portfolio returns were less volatile compared to the equity market. Moreover, in the case of all strategies, the Beta1 (β_1) coefficients were in a downward trend, similarly as the Beta1 (β_1) coefficient estimated for the overall sample. It suggests that a systematic decrease in Beta1 (β_1) in the overall sample was related especially with a decrease in systematic risk across all strategies, not with a decrease in the share of equity funds in the overall sample.

Regarding Beta2 (β_2), in the case of hedge funds, it was positive in the majority of windows, suggesting that quantitative hedge funds systematically generated higher alpha (α) compared to qualitative hedge funds. However, Beta2 (β_2) in the hedge fund group was statistically insignificant in all windows, diminishing the importance of the conclusions that have just been drawn. When it comes to absolute return funds, the Beta2 (β_2) coefficient was positive in 93.33% of windows and statistically significant in 66.67% of all windows. Statistical insignificance pertained mostly to the latest few windows. The estimated Beta2 (β_2) was marked by a long-term downward trend, which suggests that the advantage (in terms of performance generated) of quantitative absolute return funds over qualitative absolute return funds was systematically decreasing. Such results appear to be in line with those obtained in the second part of the study. Especially in the group of absolute return funds, the relative measures of portfolio performance indicated that the application of quantitative portfolio management processes may provide advantage (in terms of performance generated) over traditionally managed portfolios.

In the case of equity funds, the Beta2 (β_2) coefficient was positive in 60.00% of the windows and statistically significant in 46.67% of all windows. Positive Beta2 (β_2) could be observed especially in the most recent windows. What is more, especially in these windows, Beta2 (β_2) was statistically significant. The results obtained are similar to those of the second part of the study, according to which, quantitative equity funds more often outperformed qualitative equity funds.

In the sample of mixed asset funds, the Beta2 (β_2) coefficient was negative in all windows and statistically significant in 80.00% of all windows. The results obtained for mixed asset funds differ substantially from those obtained for the other groups, as, so far, positive Beta2 (β_2) constituted the majority of windows. However, such results are in line with those in the second part of the study, according to which, qualitative mixed asset funds clearly more often outperformed quantitative mixed asset funds.

Taking into account that the Beta2 (β_2) coefficient for the overall sample was statistically insignificant in the majority of windows, the results obtained for different strategies separately can be surprising as, it turned out that it is strategy-dependent whether the type of fund (qualitative or quantitative) has a relationship with the alpha (α).

Moving to the last coefficient of the model, i.e., Beta3 (β_3), in the case of absolute return funds, it was statistically significant in just 13.33% of the windows (in the two most recent ones) and it was positive in these cases. Taking into account all windows, Beta3 (β_3) was positive in 40% of them. The values of Beta3 (β_3) estimated for absolute return funds oscillated around zero, suggesting that the type of fund did not affect clearly its systematic risk. Nevertheless, it should be noted that due to mostly insignificant results, such conclusions should be treated with caution.

In the sample of hedge funds, Beta3 (β_3) was statistically significant in 53.33% of windows and was always negative. Statistically significant cases could be observed in the latest windows. The results obtained indicate that quantitative hedge funds regularly had lower systematic risk compared to qualitative hedge funds. However, it should be noted that these conclusions are statistically valid only for about half of the windows (the most recent ones).

In the case of mixed asset funds, Beta3 (β_3) was always positive and statistically significant in 80.00% of all windows. The results obtained for this group differ much from the results obtained for absolute return and hedge funds. In the long term, Beta3 (β_3) tended to increase, suggesting that quantitative mixed asset funds had higher and higher exposure to systematic risk compared to qualitative mixed asset funds. Similar conclusions can be drawn in the case of equity funds. In their sample, Beta3 (β_3) also was always positive; however, it was statistically significant even in more cases, i.e., in 93.33% of the windows. Nevertheless, in the long term, Beta3 (β_3) of equity funds seemed to fall as opposed to Beta3 (β_3) of mixed asset funds.

Results by region

The modified CAPM model also has been estimated separately for four most numerous groups of funds distinguished taking into account the geographic region of a primary investment focus. It has been done in order to answer a supplementary research question of whether differences in performance between quantitative and qualitative funds differ between the groups of funds distinguished in terms of the region of a primary investment focus. Hence, Figure 8.5. presents R-squared, adjusted R-squared and the p-value of the F-test of the modified CAPM model estimated in each 84-month rolling window for each of four most numerous regions of a primary investment focus separately with the use of a pooled OLS regression.

Referring to Figure 8.5., in the majority of cases, the highest R-squared values feature a group of funds primarily investing in Northern America. They range from 26.78% to 47.99% with an average value of 38.71%. By the window ending in 2013, the R-squared of these funds tended to increase reaching a maximum value of 47.99%; however, in the following windows, R-squared started to decrease. It is worth noting that in the last window, R-squared recovered significantly. A similar behaviour of R-squared in the last window pertained to the other groups, too. Although a group of funds primarily investing in Northern America had the highest R-squared out of all four groups, the goodness of fit of estimated models to actual data can be considered weak/moderate depending on the window. The goodness of fit of the other groups can be rather considered weak.

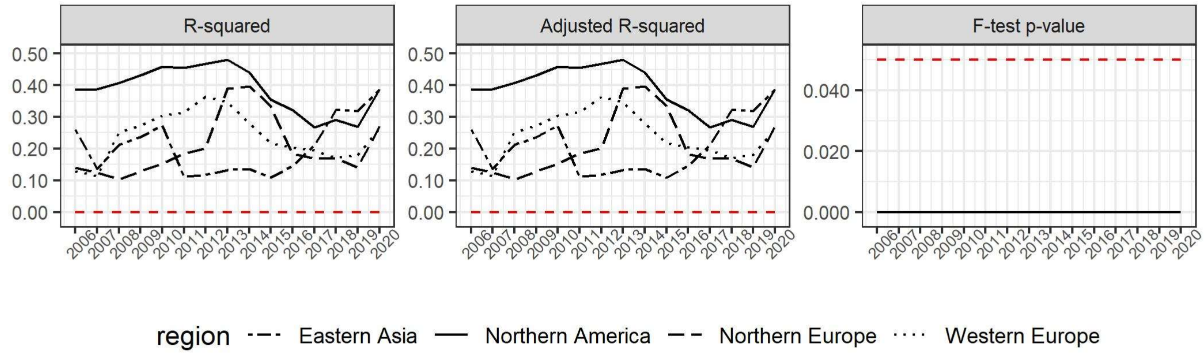

Fig. 8.5. R-squared, adjusted R-squared and the p-value of the F-test of the modified CAPM model estimated in each 84-month rolling window for each of four most numerous regions of a primary investment focus separately with the use of a pooled OLS estimation method. Source: Author's own study

A similar behaviour (but lower levels) of R-squared featured the groups of funds primarily investing in Western Europe and Northern Europe. The R-squared of funds primarily investing in Western Europe ranged from 11.34% to 36.36% with an average value of 24.03%. The R-squared of funds primarily investing in Northern Europe ranged from 10.38% to 39.59% with an average value of 20.60%. The R-squared of funds primarily investing in Eastern Asia behaved much differently, as it tended to rise starting from the window ending in 2014. Its values ranged from 10.89% to 38.53%, with an average value of 20.71%. The values of the adjusted R-squared are very similar to the values of the R-squared. The p-value of the F-test indicates that the models provide a better fit than the intercept-only model.

Moving to the estimated coefficients of the models, Figure 8.6. presents the parameters and the p-values of the parameters of the modified CAPM model, estimated in each 84-month rolling window for each of four most numerous regions of a primary investment focus separately with the use of a pooled OLS regression. The alpha (α) parameter is negative most of the time in the case of the groups of funds primarily investing in Northern America, Northern Europe, and Western Europe. In the case of funds primarily investing in Northern America, alpha (α) is negative and statistically significant in 93.33% of windows and appears to fall in the long term. It suggests that funds from this group systematically generate worse and worse results compared to the equity market.

In the case of funds primarily investing in Western Europe, alpha (α) is negative in all windows and statistically significant in 86.67% of all windows. However, it appears to rise in the long term starting from the window ending in 2008. Such results allow for stating that funds from this group systematically generate worse results compared to the equity market. Nevertheless, as opposed to funds primarily investing in Northern America, their performance gets better in the long run.

As far as funds primarily investing in Northern Europe are concerned, their alpha (α) is negative in 80.00% of the windows and statistically significant in 86.67% of all windows. What is more, it appears to increase in the long term starting from the window ending in 2014. Earlier, it seemed to decrease in the long term. In the last three windows, it was even positive and statistically significant, suggesting the actual improvement of performance generated by funds from this group. Regarding funds primarily investing in Eastern Asia, alpha (α) is negative in 46.67% of the windows and statistically significant in 66.67% of all windows. Moreover, it appears to rise in the long term starting from the window ending in 2012. Earlier, it appeared to decrease severely in the long run. Similarly as in the case of Western Europe and Northern Europe, the performance of funds primarily investing in Eastern Asia recovers from a certain window. This constitutes a major difference between them and funds primarily investing in Northern America, which generate systematically decreasing performance compared to a passive investment in the market portfolio.

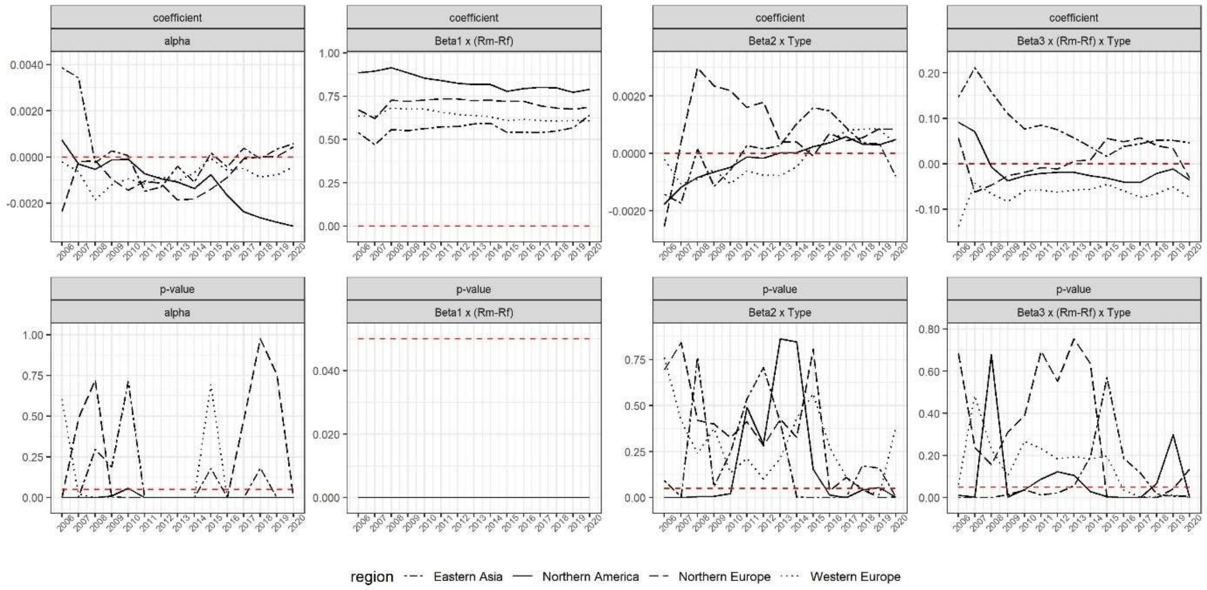

Fig. 8.6. Parameters and the p-values of the parameters of the modified CAPM model, estimated in each 84-month rolling window for each of four most numerous regions of primary investment focus separately with the use of a pooled OLS estimation method. Source: Author's own study

Regarding the Beta1 (β_1) coefficient, a group of funds primarily investing in Northern America is exposed to the highest systematic risk of the four groups examined. However, funds from this group appear to decrease their market dependence in the long run. A group of funds with the second largest Beta1 (β_1) coefficients was a group primarily investing in Northern Europe. For the most part, the systematic risk of this group appears to remain at an unchanged level. A group of funds with the third largest Beta1 (β_1) coefficients was a group primarily investing in Western Europe. Similarly as in the case of the group of funds primarily investing in Northern America, funds primarily investing in Western Europe appear to decrease their market dependence in the long run. When it comes to a group of funds with the lowest Beta1 (β_1) coefficients, the lowest systematic risk exposure featured a group primarily investing in Eastern Asia. It is the only group with a slightly rising equity market dependence in the long term. In the case of all regions, the values of the estimated Beta1 (β_1) coefficients suggest that portfolio returns are less volatile compared to the equity market. To sum up, the results pertaining to Beta1 (β_1) and presented in Figure 8.6. indicate many differences between the regions in terms of systematic risk exposure. It is also worth mentioning that all estimated Beta1 (β_1) coefficients are statistically significant, increasing the importance of conclusions drawn.

Moving onto the most important coefficient in terms of a verified main hypothesis, i.e., Beta2 (β_2), funds primarily investing in Northern Europe had the highest percentage of positive Beta2 (β_2) coefficients of 86.67%. However, their percentage of statistically significant windows was low and equalled just 26.67%. In all statistically significant cases, the Beta2 (β_2) coefficients were positive. An even lower percentage of statistically significant windows of 13.33% could be observed in the case of funds primarily investing in Western Europe. Also, in the case of this group, all statistically significant Beta2 (β_2) coefficients were positive. However, as opposed to the Northern European group, most of the Beta2 (β_2) coefficients (60%) were negative. In the case of both aforementioned groups, statistically significant Beta2 (β_2) coefficients could be observed especially in the latest windows. It suggests that in the latest windows some significant differences (in terms of performance) between quantitative and qualitative funds have emerged. It turned out that quantitative funds outperformed qualitative funds in a statistically significant way.

When it comes to funds primarily investing in the region of Eastern Asia, Beta2 (β_2) was positive in 66.67% of the windows (especially in the latest ones) and statistically significant in 40.00% of all windows. Similarly as in the case of funds primarily investing in Northern and Western Europe, statistically significant Beta2 (β_2) coefficients could be observed especially in the latest windows.

As far as funds primarily investing in Northern America are concerned, Beta2 (β_2) was positive in 53.33% of windows. In 60.00% of all windows it was statistically significant. In half of these cases, Beta2 (β_2) was positive. Statistically significant parameters could be observed especially in the oldest and the latest windows. In the oldest windows, which have been statistically significant, Beta2 (β_2) was negative. On the other hand, in the latest windows, which were statistically significant, Beta2 (β_2) was positive. Thus, also in the case of funds primarily investing in Northern America, quantitative funds started to outperform qualitative funds in the latest windows.

Moving to the Beta3 (β_3) coefficient, which refers to the differences between quantitative and qualitative funds in systematic risk, in the case of funds primarily investing in Northern and Western Europe, Beta3 (β_3) was statistically significant in just 33.33% of windows. Statistically significant cases pertained to the latest windows. Despite this similarity between the two aforementioned groups, they differ significantly. In the group of funds primarily investing in Northern Europe, 53.33% of the estimated Beta3 (β_3) coefficients are positive. These are mostly the latest windows, which are also statistically significant. Thus, when it comes to funds primarily investing in Northern Europe, in the latest windows, quantitative funds appeared to be exposed to higher systematic risk compared to qualitative funds. As far as funds primarily investing in Western Europe are concerned, the opposite was true.

Beta3 (β_3) estimated for the group of funds primarily investing in Northern America was negative in 86.67% of the windows. In the case of this group, 60% of the estimated Beta3 (β_3) coefficients were statistically significant and they were mostly negative, suggesting that quantitative funds appeared to be exposed to lower systematic risk compared to qualitative funds. Similar conclusions could be drawn on the basis of the results obtained for the group of funds primarily investing in Western Europe.

The results received for funds primarily investing in Eastern Asia allow for drawing clearly different conclusions to those drawn on the basis of the results obtained for the groups of funds primarily investing in Northern America and Western Europe. In the case of funds primarily investing in Eastern Asia, all estimated Beta3 (β_3) coefficients were positive. However, 66.67% of them were statistically significant. Nevertheless, the results obtained for this group allow for stating that in most cases, quantitative funds were exposed to systematic risk more compared to qualitative funds.

8.2. Treynor-Mazuy model (TM)

This section presents the results of the modified Treynor-Mazuy model (TM) estimation. The modified TM model (already discussed in Section 5.3.3.) can be described by the equation:

$$R_{it} - Rf_t = \alpha + \beta_1(Rm_t - Rf_t)^2 + \beta_2(Rm_t - Rf_t) + \beta_3 Type_i + \beta_4 Type_i(Rm_t - Rf_t)^2 + \beta_5 Type_i(Rm_t - Rf_t) + \varepsilon \quad (5.2.)$$

The same as in the case of the modified CAPM model, the modified TM model was estimated for the overall sample (the one including all funds), separately for each of four groups of funds distinguished in terms of the main strategy according to the Lipper Global Classification scheme and separately for each of four most numerous groups of funds distinguished in terms of the geographic region of a primary investment focus.

Overall results

The same as in the case of the modified CAPM model, the modified TM model was estimated using a pooled OLS regression. Random effects and fixed effects models were also considered. However, the results of the Breusch and Pagan Lagrange multiplier test for random effects indicated that the random effects model would be applicable in the case of 6 out of 15 windows (40.00% of windows). The results of the F test for no fixed effects indicated that the fixed effects model would be applicable in the case of 7 out of 15 windows (46.67% of windows). The results of the aforementioned tests indicated that the random and fixed effects models would be applicable in the minority of windows. Thus, it was decided to apply a pooled OLS regression. Nevertheless, in the case of the overall sample, the results of both a pooled OLS regression and fixed effect model will be presented in order to check if the models provide much different estimates. Standard errors in the pooled OLS regression were corrected using the Newey-West procedure with automatic lag selection.

Figure 8.7. presents R-squared, adjusted R-squared and the p-value of the F-test of the modified TM model estimated in each 84-month rolling window for the overall sample with the use of a pooled OLS regression and fixed effects model. The results of the estimations (in terms of goodness of fit) of the fixed effects model and pooled OLS regression are very similar. Moreover, the results obtained for the modified TM model are very similar to those obtained for the modified CAPM model. The R-squared of the fixed effects model ranges from 20.88% to 35.38% with an average result of 28.04%. In the case of a pooled OLS regression R-squared ranges from 20.82% to 35.13% with an average result of 27.91%. The adjusted R-squared of the fixed effects model ranges from 19.81% to 34.46% with an average result of 27.02%. In the case of a pooled OLS regression, the adjusted R-squared ranges from 20.82% to 35.13% with an average result of 27.91%. The results obtained indicate that both models provide a very similar goodness of fit.

Taking into account the results obtained, the models appear to be fitted to the actual data rather weakly. Similarly as in the case of the modified CAPM model, it is not easy to spot any long-term trends in the behaviour of goodness-of-fit measures, which have been applied in this study. Nevertheless, they seem to fall in the long term starting from the window ending in 2009 up to the window ending in 2018. In earlier and subsequent windows, the goodness of fit of the estimated TM models to actual data appeared to increase. In the case of both models, the p-value of the F-test indicates that the models provide a better fit than the intercept-only model.

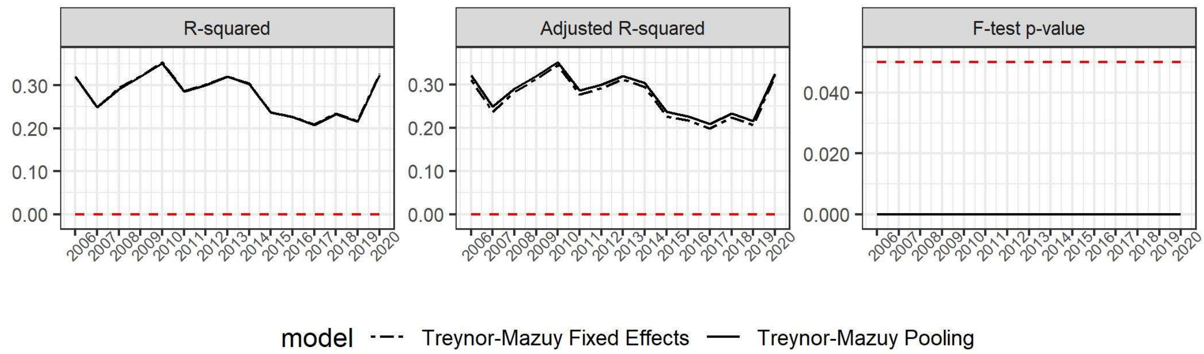

Fig. 8.7. R-squared, adjusted R-squared, and the p-value of the F-test of the modified TM model estimated in each 84-month rolling window for the overall sample with the use of a pooled OLS regression and fixed effects model. Source: Author’s own study

Moving to the estimated parameters of the modified TM model presented in Figure 8.8., alpha (α) decreased in the long term, similarly to alpha (α) estimated in the modified CAPM model. In 73.33% of the windows, it was negative. Moreover, in 80.00% of all windows, it was statistically significant. As opposed to alpha (α) estimated in the modified CAPM model, alpha (α) estimated in the modified TM model was more often positive in first windows. The results obtained allow for stating that the performance of all examined funds diminished over the windows and became significantly worse compared to the performance of a passive investment in the equity market portfolio.

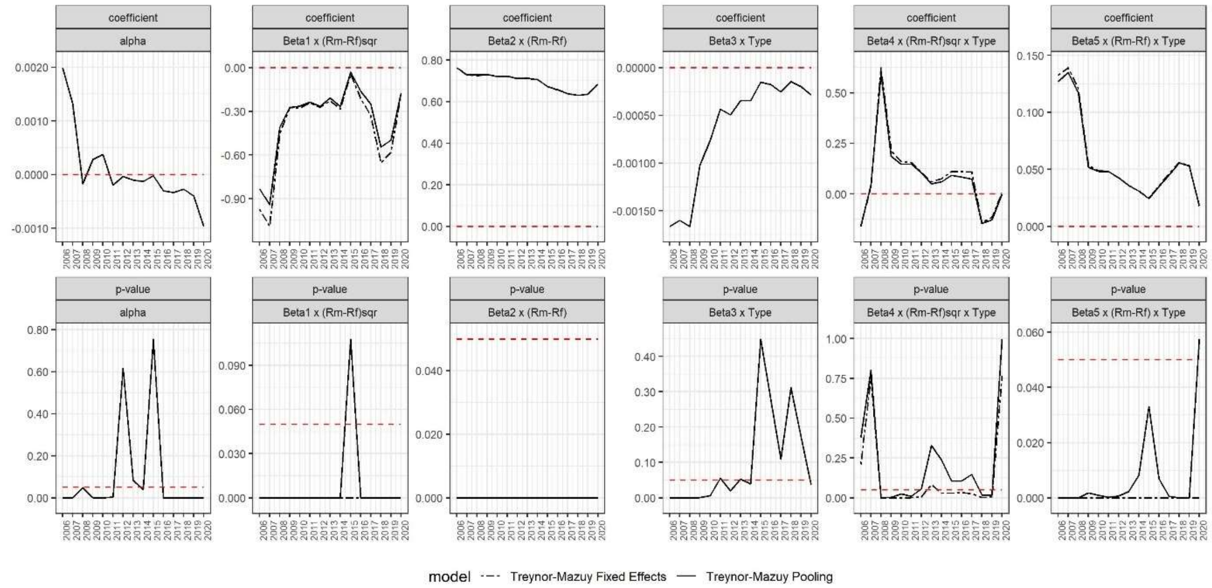

Fig. 8.8. Parameters and the p-values of the parameters of the modified TM model, estimated in each 84-month rolling window for the overall sample with the use of a pooled OLS regression and fixed effects model. Source: Author's own study

Regarding the Beta1 (β_1) coefficient, it was always negative in the case of both models and statistically significant in almost all windows. In most cases, the estimated Beta1 (β_1) coefficients did not differ much between the models. The negative and statistically significant values of the Beta1 (β_1) coefficient may suggest that funds included in the overall sample do not implement a correct strategy of active portfolio management and make mistakes in adjusting the level of a systematic risk to expected market conditions.

When it comes to the estimated values of Beta2 (β_2), they are very similar to those estimated in the modified CAPM model (in the case of the modified CAPM model, an analogical coefficient was Beta1 (β_1)). The Beta2 (β_2) coefficient was statistically significant in all windows and its values ranged from about 0.63 to about 0.76, which means that all examined funds were less volatile compared to market. Figure 8.8. also suggests that Beta2 (β_2) is in a downward trend, which means that a systematic risk of funds systematically decreases.

Regarding Beta3 (β_3), which refers to differences in selectivity skills between qualitative and quantitative funds, its all estimated values are negative and statistically significant in 53.33% of all windows. However, in the long term, Beta3 (β_3) appears to be rising. Such results suggest that only in about 50% of all windows, a type of fund (qualitative/qualitative) had a statistically significant relationship with alpha (α). Statistically significant Beta3 (β_3) coefficients appeared especially in the oldest windows. In other words, in this case, in all windows, quantitative funds performed worse compared to qualitative funds. Of course, the importance of this conclusion is decreased in about half of the windows due to statistical insignificance of the estimates. Similar conclusions could be drawn in the case of the modified CAPM model. Nevertheless, a number of statistically significant cases in the TM model were higher.

Beta4 (β_4), which refers to differences in market-timing skills between qualitative and quantitative funds, was positive in 80% of windows in a fixed effects model and in 73.33% of windows in a pooled OLS regression. However, in a fixed effects model, Beta4 (β_4) was statistically significant in 73.33% of windows and in the pooled OLS regression in just 40.00% of windows. The results obtained may suggest that according to a fixed effects model, in most cases, the type of fund in a statistically significant way affected Beta1 (β_1). In the majority of statistically significant windows, quantitative portfolio management techniques positively affected the implementation of a correct strategy of the active portfolio management and decreased mistakes in adjusting the level of a systematic risk to expected market conditions. Nevertheless, it is worth noting that the advantage of the quantitative funds over the qualitative ones decreased over the windows.

When it comes to Beta5 (β_5), similarly as in the case of the modified CAPM model (in the case of the modified CAPM model an analogical coefficient was Beta3 (β_3)), the values of this coefficient were positive; however, they were also decreasing in the long term. Moreover, they were statistically significant in almost all cases. The results obtained suggest that a type of fund was important in terms of systematic risk. Quantitative funds were more risky in this matter; nevertheless, the differences in systematic risk exposure between quantitative and qualitative funds were decreasing over the windows.

Results by strategy

Referring to a supplementary research question of whether differences in performance between quantitative and qualitative funds differ between the groups of funds distinguished in terms of strategy, the following part of this section discusses the results of the estimation of the modified TM model for different strategies separately. Figure 8.9. presents R-squared, adjusted R-squared and the p-value of the F-test of the modified TM model estimated in each 84-month rolling window for each strategy separately with the use of a pooled OLS regression. The results presented in Figure 8.9. are very similar to those, which could be observed in the case of the modified CAPM (Figure 8.3.). Again, despite the fact that equity funds are marked by the highest values of goodness-of-fit measures, fit of their estimated model to actual data can be rather considered weak. The goodness of fit of the models of the other strategies is only weaker.

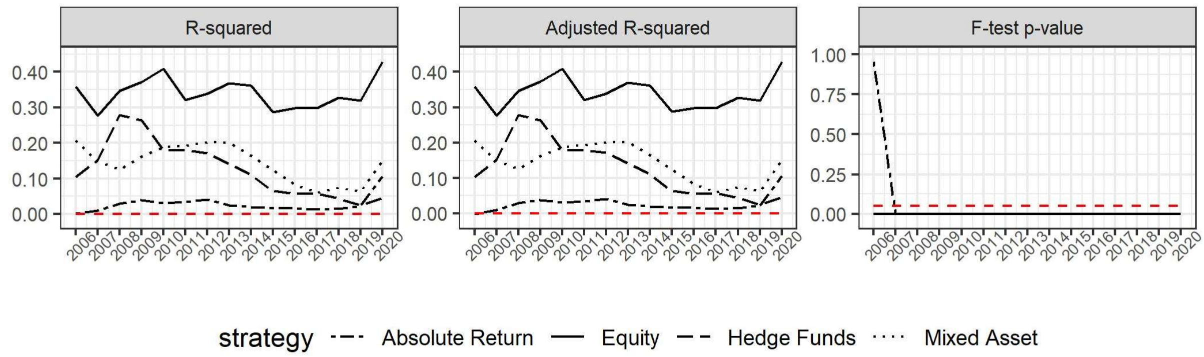

Fig. 8.9. R-squared, adjusted R-squared, and the p-value of the F-test of the modified TM model estimated in each 84-month rolling window for each strategy separately with the use of a pooled OLS regression. Source: Author's own study

Moving to the estimated parameters of the modified TM model, Figure 8.10. presents parameters and p-values, estimated in each 84-month rolling window for each strategy separately with the use of a pooled OLS regression. The alpha (α) coefficient in the group of hedge funds was positive in the case of all windows and statistically significant in 80.00% of them. Nevertheless, in the long term, it appears to decrease, similarly as in the case of the modified CAPM model. Such results suggest that the examined hedge funds systematically outperformed the market; however, their advantage regularly decreased. In the case of the other three groups, the majority of the alpha (α) coefficients were negative, suggesting that absolute return, equity, and mixed asset funds were mostly outperformed by the market. Again, the behaviour of the alpha (α) coefficients was similar in the case of the modified CAPM model. In the case of absolute return funds, the alpha (α) was negative in 93.33% of the windows, but statistically significant in just 33.33% of all windows. In the group of mixed asset funds, the alpha (α) was negative in 86.67% of the cases and statistically significant in 73.33% of all windows. In the case of equity funds, the alpha (α) was negative in 66.67% of the windows and statistically significant in 80.00% of all windows. The negative alphas (α) of equity funds especially pertained to the latest windows. Similarly as in the case of the hedge fund group, the performance of equity funds clearly decreased in the long term.

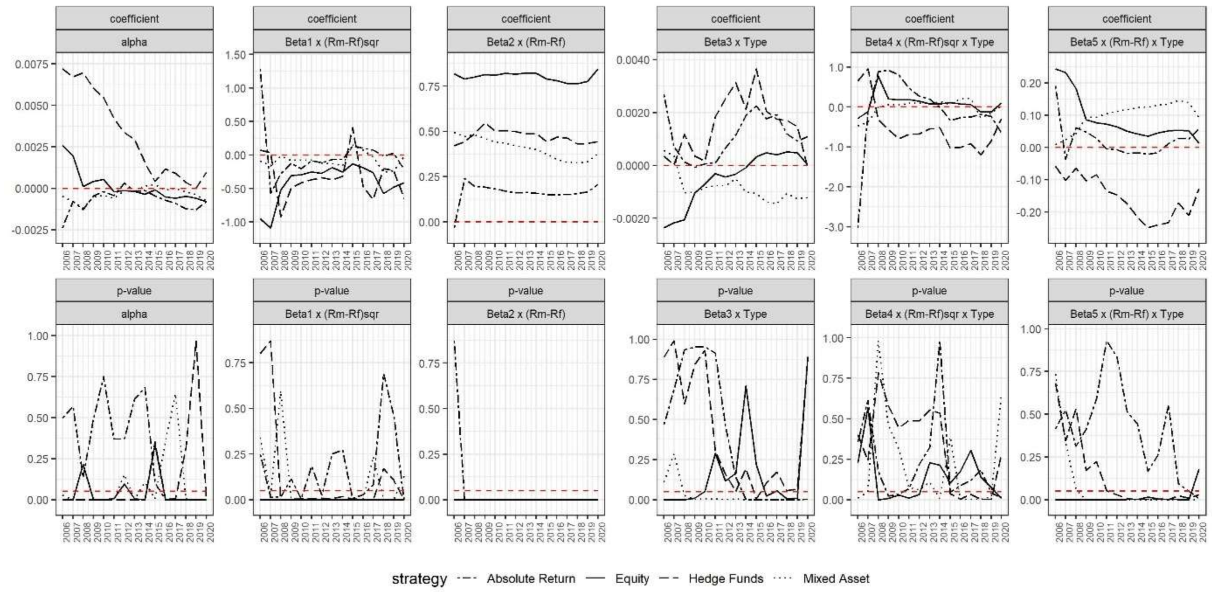

Fig. 8.10. Parameters and the p-values of the parameters of the modified TM model, estimated in each 84-month rolling window for each strategy separately with the use of a pooled OLS regression. Source: Author's own study

Beta1 (β_1) was negative in the majority of cases in each of the four groups. Such results may suggest that funds included in each of the four groups do not implement a correct strategy of active portfolio management and make mistakes in adjusting the level of systematic risk to expected market conditions. Similar results could be observed in the case of the overall sample.

The results obtained for equity funds appear to resemble the most the ones obtained for the overall sample. Beta1 (β_1) of equity funds was negative and statistically significant in all windows. In the groups of hedge funds and mixed asset funds, Beta1 (β_1) was negative in 80.00% and 86.67% of cases, respectively, and statistically significant in 73.33% of all windows. A group of absolute return funds had the lowest number of the negative Beta1 (β_1) coefficients reaching 66.67%. However, a number of statistically significant Beta1 (β_1) coefficients was also the lowest and reached just 46.67%. Absolute return funds had the highest market-timing skills across all groups, especially in the last few windows. However, the importance of this conclusion is decreased due to the low percentage of statistically significant results.

Regarding Beta2 (β_2) coefficients, they behave over the windows and reach levels similarly as in the case of those estimated in the modified CAPM model (in the case of the CAPM model an analogical coefficient was Beta1 (β_1)). In almost all cases, Beta2 (β_2) was statistically significant as well.

When it comes to Beta3 (β_3), some major differences between strategies can be observed. The results received appear to resemble those obtained in the case of the modified CAPM model estimation (the analogical coefficient in the modified CAPM model was Beta2 (β_2)), especially in terms of the number of positive and statistically significant cases. A group of mixed asset funds had the highest percentage of statistically significant Beta3 (β_3) coefficients of 86.67%. All of these cases were negative, suggesting that quantitative funds had a lower alpha (α) compared to qualitative funds. What is more, in the long term, Beta3 (β_3) appeared to fall, indicating that quantitative funds performed worse and worse compared to qualitative funds. On the other hand, almost all Beta3 (β_3) coefficients (93.33%) in the hedge fund group were positive, suggesting that quantitative funds performed better compared to qualitative funds. Nevertheless, the Beta3 (β_3) coefficients of hedge funds were statistically significant in just one window. Thus, this conclusion should be treated with caution. Almost all the Beta3 (β_3) coefficients (93.33%) were also positive in the group of absolute return funds. However, as opposed to the hedge fund group, the percentage of efficient windows was much higher and amounted to 46.67%. Statistically significant cases pertained to the latest windows in particular. Thus, the results obtained allow for stating that especially in the latest windows, quantitative hedge funds performed better compared to qualitative hedge funds. Moving to equity funds, the estimated Beta3 (β_3) coefficients were positive in 40% of windows. Positive cases pertained to the latest periods. In 46.67% of windows, the Beta3 (β_3) coefficients were statistically significant. It was the only group with a clear long-term upward trend suggesting the increase of the advantage of quantitative funds over qualitative funds in terms of performance. The estimates of Beta3 (β_3) in the modified TM model allow for drawing conclusions similar to those drawn from the estimates of the analogical coefficient in the modified CAPM model, i.e., Beta2 (β_2). The results of the Beta3 (β_3) estimates appear to be also in line with the results of the second part of the study.

As far as Beta4 (β_4) is concerned, the results indicate that strategies are diverse in terms of differences between quantitative and qualitative funds in market-timing skills. However, they share a common feature, namely, in the long term, the Beta4 (β_4) coefficient appears to decrease across all strategies, suggesting a decreasing advantage of quantitative funds. The most similar estimates of Beta4 (β_4) were obtained for equity and mixed asset funds. The estimated coefficients for these groups were mostly positive (73.33%), suggesting that in most cases, the market-timing skills of quantitative funds were higher compared to qualitative funds. However, such conclusions should be approached with caution, as the percentage of statistically significant cases is not high, reaching 40.00% in the case of equity funds and 46.67% in the case of mixed asset funds. An even lower percentage of statistically significant cases (33.33%) can be observed in the case of absolute return and hedge funds. When it comes to hedge funds, the vast majority of estimated Beta4 (β_4) coefficients was negative, suggesting lower market-timing skills of quantitative funds compared to qualitative funds. This conclusion holds (statistically significant windows) especially in the case of the latest windows. Absolute return funds were also marked by the majority of negative coefficients. However, their percentage was much less and amounted to 60.00%.

When it comes to the Beta5 (β_5) coefficient, similarly as in the case of Beta4 (β_4), the most similar estimates of Beta5 (β_5) were obtained for equity and mixed asset funds. In all windows, Beta5 (β_5) was positive, suggesting that quantitative funds were more exposed to systematic risk than qualitative funds. However, there were also some differences between equity and mixed asset funds. Namely, in the long term, the exposure of quantitative equity funds to systematic risk decreased in comparison to qualitative funds. On the other hand, in the long term, the exposure of quantitative mixed asset funds to systematic risk increased in comparison to qualitative funds. These conclusions appear to be reliable, as in the vast majority of cases, the results were statically significant (in 93.33% of the windows in the case of equity funds and in 80.00% of the windows in the case of mixed asset funds). The results of hedge funds differ much compared to two previously discussed groups. In all windows, they were negative, suggesting that quantitative funds were less exposed to systematic risk than qualitative funds. Beta5 (β_5) estimated for hedge funds was statistically significant in 60.00% of windows. Statistically significant cases pertained to the latest windows. Thus, conclusions made refer to them in particular. Only one statistically significant Beta5 (β_5) was estimated for absolute return funds. It pertained to the last window. Beta5 (β_5) was positive in 53.33% of cases. Nevertheless, in this situation, it is difficult to draw any reliable conclusions pertaining to the behaviour of this parameter over the windows. In general, Beta5 (β_5) estimated for the modified TM model of each strategy allows for drawing conclusions similar to those drawn on the basis of the analogical coefficient in the modified CAPM model, i.e., Beta3 (β_3).

Results by region

The modified TM model has also been estimated separately for four most numerous groups of funds distinguished in terms of the geographic region of a primary investment focus. It has been done in order to answer a supplementary research question of whether differences in performance between quantitative and qualitative funds differ between the groups of funds distinguished in terms of the region of a primary investment focus. Figure 8.11. presents R-squared, adjusted R-squared, and the p-value of the F-test of the modified TM model estimated in each 84-month rolling window for each of four most numerous regions of primary investment focus separately with the use of a pooled OLS regression.

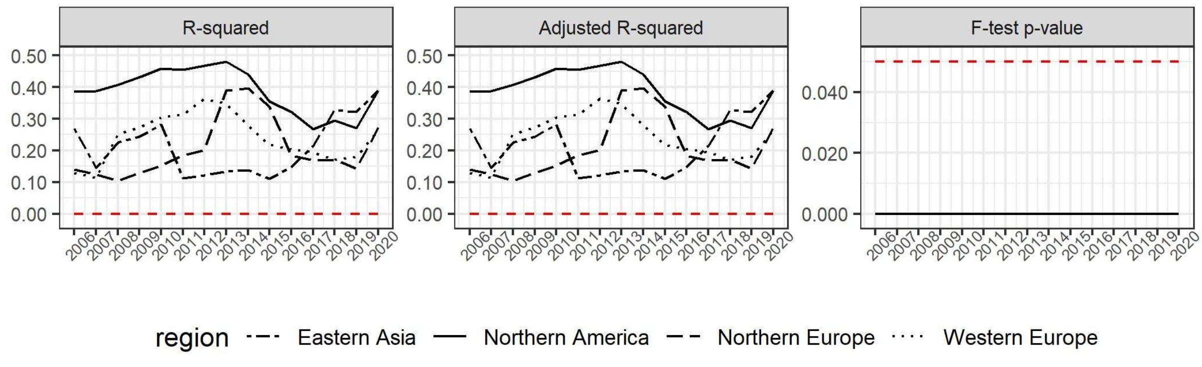

Fig. 8.11. R-squared, adjusted R-squared, and the p-value of the F-test of the modified TM model estimated in each 84-month rolling window for each of four most numerous regions of primary investment focus separately with the use of a pooled OLS regression. Source: Author's own study

The results presented in Figure 8.11. are similar those obtained for the modified CAPM model estimated for each region separately (Figure 8.5.). Again, in the majority of cases, the highest R-squared values feature a group of funds primarily investing in Northern America. By the window ending in 2013, the R-squared of these funds tended to increase reaching a maximum value. However, in the following windows, it started to drop. It is worth noting that in the last window, the R-squared recovered significantly. This behaviour of R-squared in the last window also pertained to the other groups. Although a group of funds primarily investing in Northern America had the highest R-squared of all four groups, the goodness of fit of estimated models to actual data can be considered weak/moderate depending on the window. The goodness of fit of the models in the other groups can be considered rather weak. A similar behaviour (but lower levels) of R-squared featured the groups of funds primarily investing in Western Europe and Northern Europe. The R-squared of funds primarily investing in Eastern Asia behaved much differently, as it tended to rise starting from the window ending in 2014. The values of the adjusted R-squared are very similar to the values of the R-squared. The p-values of the F-tests indicate that the models provide a better fit than the intercept-only model.

Moving to the parameters of the estimated TM model, Figure 8.12. presents parameters and p-values estimated in each 84-month rolling window for each of four most numerous groups of funds distinguished in terms of the geographic region of a primary investment focus. The alpha (α) parameter differs significantly between the regions. When comparing alphas (α) estimated in the TM model with those estimated in the CAPM model, alphas (α) estimated in the TM model were more often positive. In the case of funds primarily investing in the region of Eastern Asia, all alpha (α) parameters were positive and statistically significant. What is more, up to the window ending in 2016 they seemed to decrease and recover in the following windows. Such results suggest that funds primarily investing in Eastern Asia outperformed the market; however, their advantage systematically decreased up to the window ending in 2016. In the following windows, their advantage increased again. The situation looks differently in the case of the other three groups. The alpha (α) parameters in the group of funds primarily investing in Northern America were negative in 86.67% of the windows and statistically significant in 92.86% of the windows. Moreover, they appeared to decrease in the long term, suggesting that the performance of funds primarily investing in Northern America decreased more and more. In the groups of funds primarily investing in Northern Europe and Western Europe, the alpha (α) parameters were positive in just 40.00% and 33.33% of windows, respectively, and statistically significant in 73.33% and 66.67% of windows, respectively. The alpha (α) parameters estimated for these groups were marked by variable short-term trends. They rather oscillated around the value of 0. The results obtained for the groups of funds primarily investing in Northern and Western Europe suggest that in most cases, funds were outperformed by the market. However, due to not that high percentage of statistically significant cases these conclusions should be approached with caution.

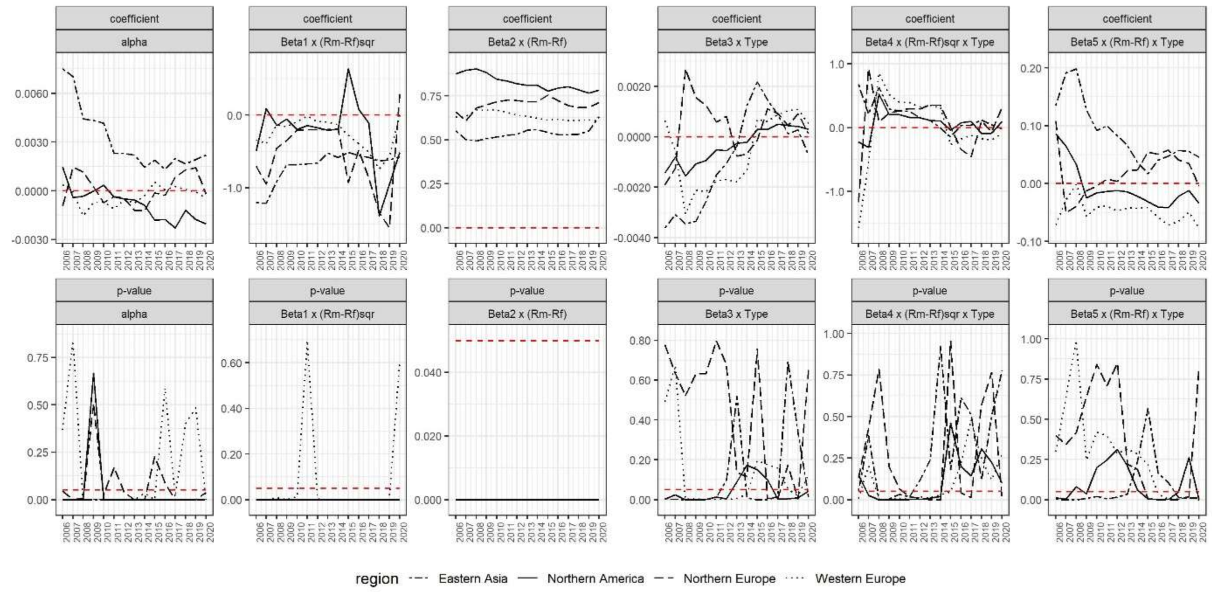

Fig. 8.12. Parameters and the p-values of the parameters of the modified TM model, estimated in each 84-month rolling window for each of four most numerous regions of primary investment focus separately with the use of a pooled OLS regression. Source: Author's own study

Regarding the Beta1 (β_1) coefficient, in the four examined groups of funds, it behaved similarly to Beta1 (β_1) of the overall sample, i.e., the majority of the Beta1 (β_1) coefficients were negative and statistically significant. Thus, the funds from all four groups do not implement a correct strategy of active portfolio management and make mistakes in adjusting the level of systematic risk to expected market conditions.

When it comes to the Beta2 (β_2) coefficient, it behaves over the windows and reaches similar levels as in the case of the analogical coefficient estimated in the modified CAPM model (in the case of the CAPM model an analogical coefficient was Beta1 (β_1)). In the case of all regions, the values of the estimated Beta2 (β_2) coefficients suggest that portfolio returns are less volatile compared to the equity market. A group of funds primarily investing in Northern America is exposed to the highest systematic risk of the four groups examined. Nevertheless, in the long term, their risk exposure decreases. The second largest Beta2 (β_2) coefficients feature a group of funds primarily investing in Northern Europe. For the most part, the systematic risk of this group appears to remain at an unchanged level. A group of funds with the third largest Beta2 (β_2) coefficients is a group of funds primarily investing in Western Europe. They appear to decrease their market dependence in the long run, similarly as a group of funds primarily investing in Northern America. The lowest systematic risk exposure features a group of funds primarily investing in Eastern Asia. It is the only group with a slightly increasing equity market dependence in the long term. In the case of almost all windows and regions, Beta2 (β_2) was statistically significant. This fact increases the importance of the conclusions drawn.

Moving to the Beta3 (β_3) coefficient, its estimates in the modified TM model share some similarities with the analogical coefficient from the modified CAPM model, i.e., Beta2 (β_2). There are also some differences between them. Regarding the similarities, the positive

Beta3 (β_3) coefficients can be observed especially in the latest windows across all groups, suggesting that quantitative funds started to outperform qualitative funds in the most recent periods. Regarding the differences, more Beta3 (β_3) coefficients were negative in the TM model compared to the estimates of the analogical coefficient in the CAPM model. In the case of the TM model, also a number of statistically significant windows was higher.

In the case of the regions of Eastern Asia and Northern America, the coefficients were negative in 60.00% of windows and statistically significant in 73.33% of windows. In the group of funds primarily investing in Western Europe, 53.33% of the Beta3 (β_3) coefficients were negative and statistically significant. Funds primarily investing in Northern Europe had the lowest percentage of statistically significant Beta3 (β_3) coefficients of 20.00%. In 33.33% of windows, the Beta3 (β_3) coefficients estimated for this group were negative. It is also worth mentioning that the Beta3 (β_3) coefficients clearly differed between the groups in terms of their levels.

When it comes to the estimates of the Beta4 (β_4) coefficient, the examined groups appear to differ in terms of the differences in the market-timing skills between quantitative and qualitative funds. However, they also appear to have some common features such as a long-term downward trend in the advantage of quantitative funds in terms of the market-timing skills. This feature could also be observed in the results obtained for the overall sample. Nevertheless, such conclusions should be approached with caution, as the percentage of statistically significant Beta4 (β_4) coefficients across the groups is not high in the modified TM model. For instance, the lowest percentage of statistically significant windows (26.67%) can be observed in the case of funds primarily investing in Eastern Asia. On the other hand, this group has the highest rate of positive windows that amounts to 80.00%. It suggests that in the majority of windows, quantitative funds were marked by better market-timing skills compared to qualitative funds. Nevertheless, due to a low rate of statistically significant windows, these conclusions should be treated with caution. A group of funds primarily investing in Northern Europe was marked by the second highest rate of the positive Beta4 (β_4) coefficients of 73.33%. In this case, the rate of statistically significant cases was higher and amounted to 46.67%. The Beta4 (β_4) coefficient estimated for a group of funds primarily investing in Northern America was even less frequently positive (66.67%). It was statistically significant in 53.33% of cases. The lowest number of the positive Beta4 (β_4) coefficients can be observed in the case of the group of funds that primarily invest in Western Europe (46.67%). Nevertheless, the results obtained for this group allow for stating the most reliable conclusions, as the percentage of statistically significant windows was the highest of all groups reaching 60.00%. Especially in the latest windows, quantitative funds had worse market timing compared to qualitative funds.

As far as Beta5 (β_5) is concerned, the results of its estimations allow for drawing similar conclusions to those made on the basis of the estimates of the analogical coefficient in the CAPM model, i.e., Beta3 (β_3). Beta5 (β_5) was always positive in the group of funds primarily investing in Eastern Asia and statistically significant in 73.33% of the windows. It was the highest percentage of positive and statistically significant Beta5 (β_5) coefficients among the four examined groups. Such results suggest that quantitative funds were exposed to higher systematic risk than qualitative funds. Nevertheless, in the long term, quantitative funds tended to become less risky compared to qualitative funds. On the other hand, in the group of funds primarily investing in Western Europe, all estimates were negative and statistically significant in just 33.33% of the windows. The Beta5 (β_5) coefficients estimated for this group suggest that quantitative funds were exposed to lower systematic risk than qualitative funds. In the long term, quantitative funds tended to become less risky compared to qualitative funds as well. However, such conclusions should be approached with caution due to the low number of statistically significant windows. A similar situation in terms of the rate of negative coefficients could be observed in the case of funds primarily investing in Northern America. In the case of this group, 80.00% of the estimated Beta5 (β_5) coefficients were negative, suggesting that quantitative funds were exposed to a lower systematic risk than qualitative funds. These conclusions should also be treated with caution, as estimated coefficients were statistically significant in 53.33% of cases. Similarly as in the case of previously discussed groups, also in the case of funds primarily investing in Northern America, in the long term, quantitative funds tended to become less risky compared to qualitative funds. Slightly different situation can be observed in the case of Beta5 (β_5) estimated in the group of funds primarily investing in Northern Europe. For the most part, the Beta5 (β_5) coefficients increased. In 66.67% they were positive, suggesting that quantitative funds were exposed to a higher systematic risk than qualitative funds. Positive cases pertained to the latest windows in particular. Again, these conclusions should be approached with caution, as not that many estimates of the Beta5 (β_5) coefficients were statistically significant.

8.3. Performance in periods of low weak-form informational efficiency of equity markets measured with the use of the CAPM and TM models

This section constitutes the expansion of the study on the performance of quantitative funds in periods of low weak-form informational efficiency of equity markets, which has been discussed in Section 7.6. The aforementioned study applied raw and excess returns, as well as the relative measures of portfolio performance in order to estimate the performance of the examined funds in periods of the lowest weak-form informational efficiency of equity markets. Such periods were selected in the first part of the study in Chapter 6. However, it should be noted that the first part of the study applied different parameters of the rolling window methodology compared to the third part of the study. Namely, in the first part of the study, all calculations were run for 60-month rolling windows with a 12-month rolling if the window contained at least 90% of observations. On the other hand, in the third part of the study, all calculations were run for 84-month rolling windows with a 12-month rolling if the window contained at least 80% of observations. This assumption pertaining to the methodology of this study constitutes some kind of simplification.

This section discusses the results of the estimations of the modified CAPM and TM models in periods of low weak-form informational efficiency of equity markets, which have been selected in the study discussed in Chapter 6. These periods are the windows ending in 2008, 2009, and 2020. Attention will be paid to coefficients referring to differences in performance between quantitative and qualitative funds, which were added to the classic versions of applied econometric models. The Beta2 (β_2) coefficient added to a classic CAPM model and standing by $Type_i$ ($\beta_2 Type_i$) informs about higher (when positive) or lower (when negative) alpha (α) generated by quantitative funds compared to qualitative funds. The same refers to the Beta3 (β_3) coefficient added to a classic TM model, as it also refers to differences in alpha (α) between quantitative and qualitative funds. The Beta4 (β_4) coefficient added to a classic TM model and standing by $Type_i(Rm_t - Rf_t)^2$ ($\beta_4 Type_i(Rm_t - Rf_t)^2$) informs about the higher (when positive) or lower (when negative) market-timing skills of quantitative funds compared to qualitative funds.

The aim of this study is to verify whether quantitative funds perform better than qualitative funds in periods of low weak-form informational efficiency of equity markets. The H3 hypothesis, which is strictly related to the aim of this study, states that quantitative funds perform better than qualitative funds in periods of low weak-form informational efficiency of equity markets. The results of this study will be discussed at the level of a whole research sample and groups distinguished in terms of strategy and the region of a primary investment focus.

Figure 8.13. presents the results of the estimations of the Beta2 (β_2) and Beta3 (β_3) coefficients, as well as their p-values for all funds together in the windows ending in 2008, 2009, and 2020. Beta2 (β_2) comes from the modified CAPM model and Beta3 (β_3) comes from the modified TM model. Both coefficients refer to differences in alpha (α) between quantitative funds and qualitative funds. Estimates for particular windows are in columns. Coefficients, their p-values, and information about the model they come from are in rows. The following figures in this section present the results in a similar way.

Moving to the analysis of estimated coefficients, in the three examined windows, quantitative funds were outperformed by qualitative funds taking into account a whole research sample. According to both models, the outperformance of quantitative funds by qualitative funds was lower in the case of the window ending in 2020. As opposed to the estimates of the Beta3 (β_3) coefficients, all the Beta2 (β_2) coefficients were statistically insignificant. Nevertheless, the statistically significant estimates of the Beta3 (β_3) coefficients allow for drawing similar conclusions. Namely, when taking into account all funds together, quantitative funds did not manage to use the inefficiencies of the market better than qualitative funds.

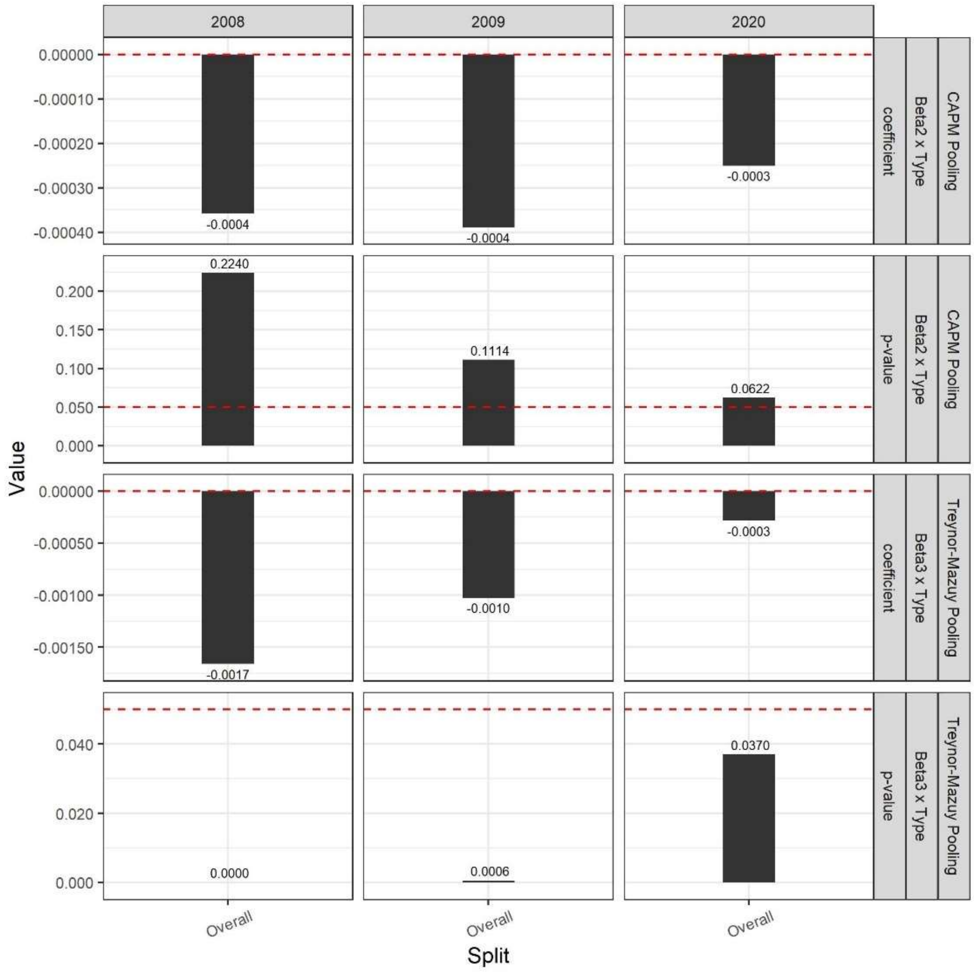

Fig. 8.13. Beta2 (β_2) (coming from the modified CAPM model), Beta3 (β_3) (coming from the modified TM model), as well as their p-values in each time window of the lowest weak-form informational efficiency of the market, estimated for all funds (overall sample). Source: Author's own study

The Beta2 (β_2) and Beta3 (β_3) coefficients estimated separately for the groups of funds distinguished in terms of strategy according to the Lipper Global Classification scheme are presented in Figure 8.14. The values of the estimated coefficients differ between the groups, models, and windows. In the window ending in 2008, the indications of both coefficients are relatively similar compared to other windows, in which the indications of the Beta2 (β_2) and Beta3 (β_3) coefficients are more different. Regarding the results in the window ending in 2008, quantitative funds in the groups of absolute return and hedge funds appear to outperform qualitative funds. In two remaining groups, i.e., equity and mixed asset funds, the opposite is true. It is worth mentioning that in both models, the estimates for absolute return and hedge funds were statistically insignificant. Thus, conclusions referring to the outperformance of qualitative funds by quantitative funds in these groups should be approached with caution. Regarding the window ending in 2009, in the groups of equity and mixed asset funds, quantitative funds performed worse again. When it comes to absolute return and hedge funds, the results varied drastically between the models. They were also statistically insignificant. In the window ending in 2020, the results were completely different compared to previously discussed windows. In both models, in the groups of hedge and mixed asset funds, quantitative funds performed worse than qualitative funds. However, the estimated coefficients in the group of hedge funds were statistically insignificant. The results obtained for the groups of absolute return and equity funds varied drastically between the models.

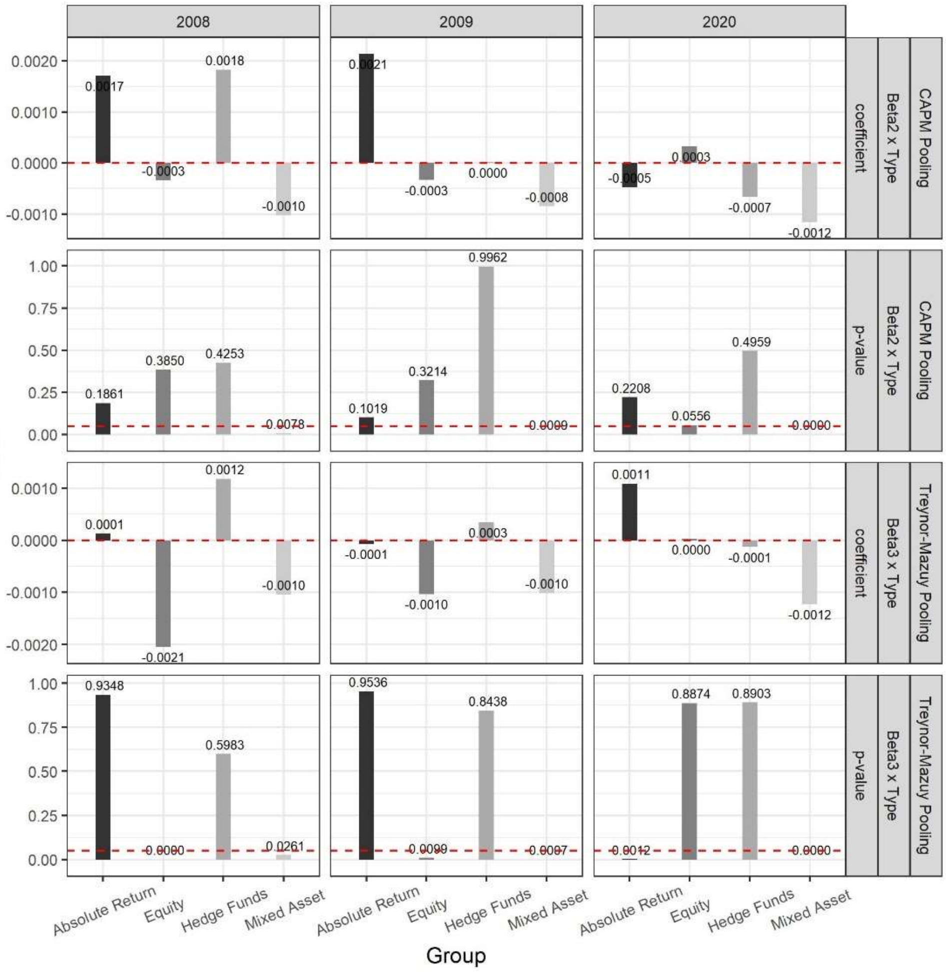

Fig. 8.14. Beta2 (β_2) (coming from the modified CAPM model), Beta3 (β_3) (coming from the modified TM model), as well as their p-values in each time window of the lowest weak-form informational efficiency of the market, estimated separately for the groups of funds distinguished in terms of strategy according to the LGC scheme. Source: Author's own study

Figure 8.15. presents the Beta2 (β_2) and Beta3 (β_3) coefficients estimated separately for four most numerous groups of funds distinguished in terms of the region of a primary investment focus. The values of the estimated coefficients differ between the groups, models, and windows. In the window ending in 2008, the estimates of both coefficients gave consistent indications in the case of funds primarily investing in Northern America, Northern Europe, and Western Europe. In the group of funds primarily investing in Northern America and Western Europe, quantitative funds were outperformed by qualitative funds. The opposite was true in the case of funds primarily investing in Northern Europe. However, in both models, the estimates pertaining to this group were statistically insignificant. The coefficients estimated for the group of funds primarily investing in Eastern Asia gave inconsistent indications in the CAPM and TM models. In the window ending in 2009, both coefficients allowed for drawing consistent conclusions in all groups. Similarly as in the case of the window ending in 2008, in

the groups of funds primarily investing in Northern America and Western Europe, quantitative funds were outperformed by qualitative funds. Also, similarly as in the case of the window ending in 2008, quantitative funds outperformed qualitative funds in the group of funds primarily investing in Northern Europe. However, the estimates for this group were statistically insignificant in the case of both models. In the window ending in 2009, the estimates pertaining to a group of funds primarily investing in Eastern Asia turned out to be consistent. They indicated that quantitative funds from this group were outperformed by qualitative funds.

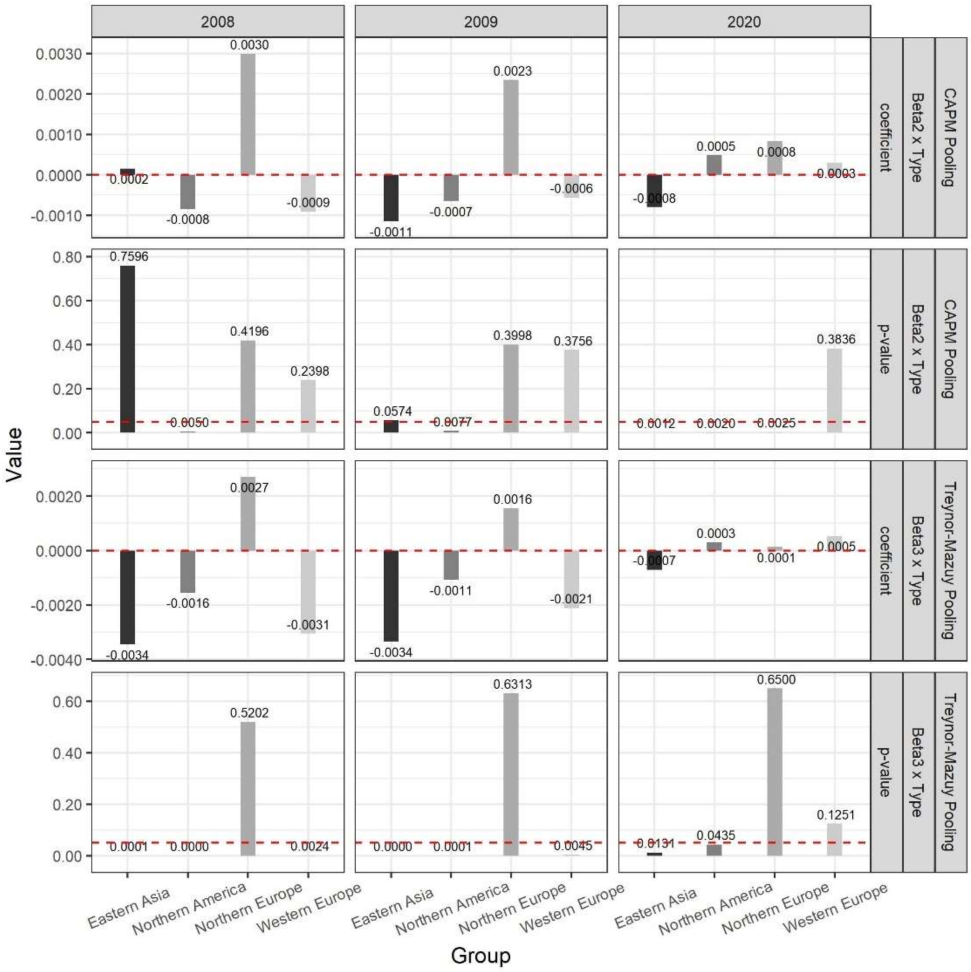

Fig. 8.15. Beta2 (β_2) (coming from the modified CAPM model), Beta3 (β_3) (coming from the modified TM model), as well as their p-values in each time window of the lowest weak-form informational efficiency of the market, estimated separately for the groups of funds distinguished in terms of the region of a primary investment focus. Source: Author's own study

Similarly as in the case of the window ending in 2009, in the window ending in 2020, both coefficients allowed for drawing consistent conclusions in all groups. However, the indications of the estimated coefficients were much different compared to previously discussed windows. Quantitative funds slightly outperformed qualitative funds in the groups of funds primarily investing in Northern America, Northern Europe, and Western Europe. The opposite was true in the case of funds primarily investing in Eastern Asia.

When it comes to differences in market timing between quantitative and qualitative funds in periods of low weak-form informational efficiency of equity markets, Figure 8.16.

presents the estimates of the Beta4 (β_4) coefficient and its p-values in the windows ending in 2008, 2009, and 2020 for all funds together (overall sample). The estimates of Beta4 (β_4) in the window ending in 2008 and 2009 suggest that quantitative funds had better market timing compared to qualitative funds. However, in the second window, a value of the measure of the market-timing skills significantly decreased. It decreased even more in the window ending in 2020 falling to about 0. However, this estimate was statistically insignificant.

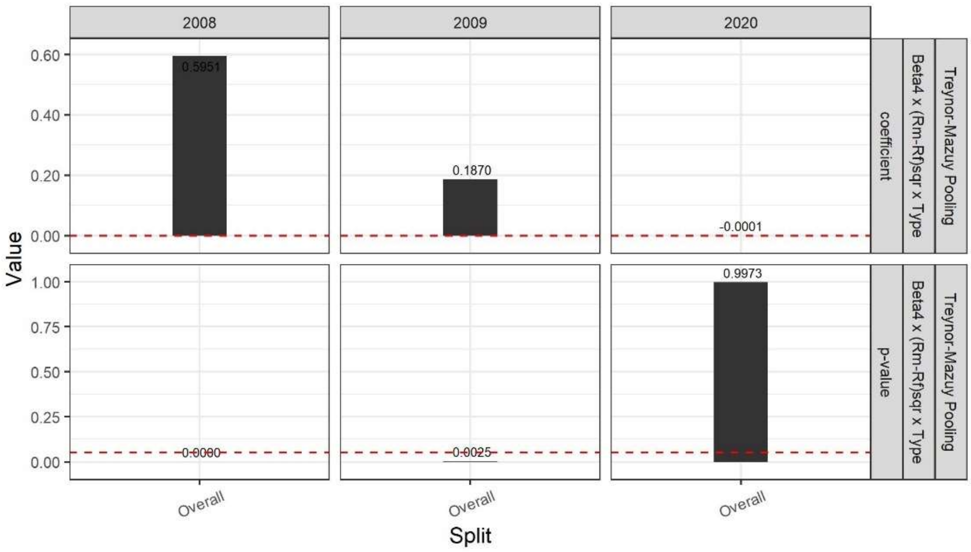

Fig. 8.16. The Beta4 (β_4) coefficients (coming from the modified TM model), as well as their p-values in each time window of the lowest weak-form informational efficiency of the market, estimated for all funds (overall sample). Source: Author's own study

When it comes to the results of the estimation of the Beta4 (β_4) coefficient separately for each group distinguished in terms of strategy, according to the results presented in Figure 8.17., the estimates in the windows ending in 2008 and 2009 allow for drawing quite similar conclusions. In the groups of absolute return, equity, and mixed asset funds, quantitative funds turned out to have better market timing compared to qualitative funds. The opposite was true in the case of hedge funds. However, the estimates pertaining especially to hedge and mixed asset funds were statistically insignificant. The estimates for the groups of equity, hedge, and mixed asset funds in the window ending in 2020 allow for drawing conclusions similar to those drawn from the estimates in previously discussed windows. However, the results obtained for absolute return funds are completely different compared to previous windows, suggesting that in the window ending in 2020, quantitative absolute return funds had worse market timing compared to qualitative funds.

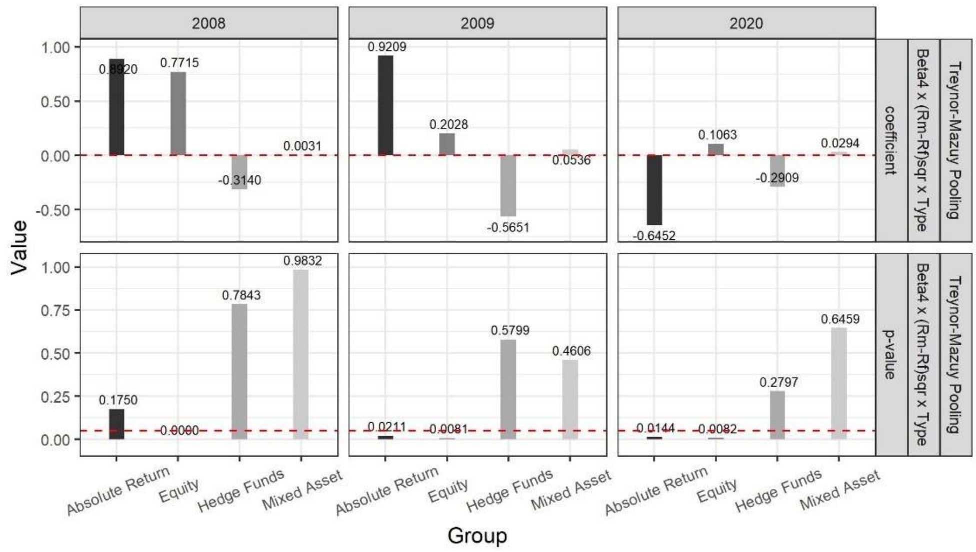

Fig. 8.17. The Beta4 (β_4) coefficients (coming from the modified TM model), as well as their p-values in each time window of the lowest weak-form informational efficiency of the market, estimated separately for the groups of funds distinguished in terms of strategy according to the LGC scheme. Source: Author's own study

Moving to the estimates of the Beta4 (β_4) coefficient separately for the four most numerous groups distinguished in terms of the region of a primary investment focus, according to Figure 8.18., the estimates in the windows ending in 2008 and 2009 allow for drawing quite similar conclusions. In the four examined groups, quantitative funds had better market-timing skills than qualitative funds. However, especially in the case of the window ending in 2008, some substantial differences between quantitative and qualitative funds could be observed. It is also worth mentioning that the estimates of Beta4 (β_4) in the group of funds primarily investing in Northern Europe were statistically insignificant. Thus, the conclusions drawn on their basis should be approached with caution. Much different conclusions can be drawn on the basis of the results in the window ending in 2020. The advantage of quantitative funds over qualitative funds, which could be observed in the previous windows, decreased substantially. In the groups of funds primarily investing in Eastern Asia and Western Europe, quantitative funds had lower market-timing skills than qualitative funds. However, this conclusion should be treated with caution, as the estimates in these groups were statistically insignificant in particular. In the case of the remaining two groups, the opposite was true.

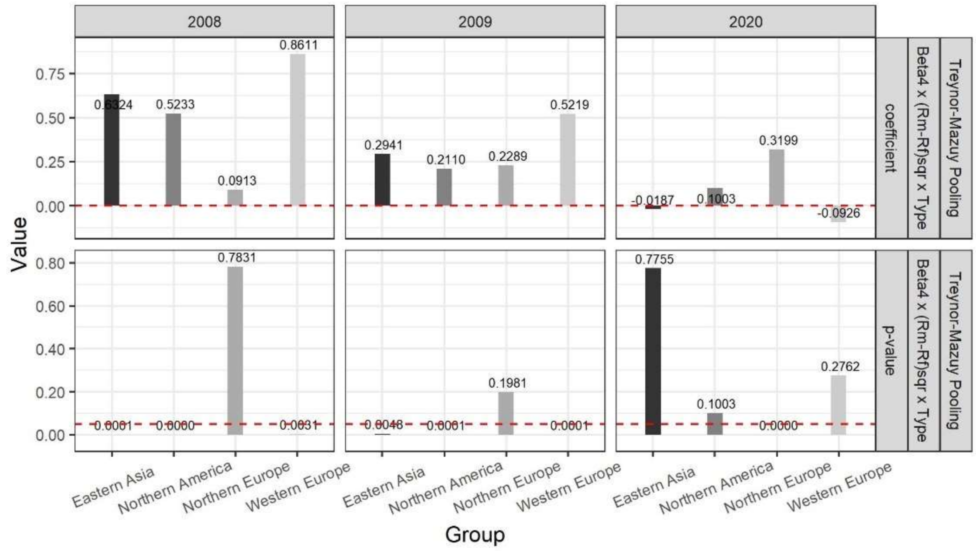

Fig. 8.18. The Beta4 (β_4) coefficients (coming from the modified TM model), as well as their p-values in each time window of the lowest weak-form informational efficiency of the market, estimated separately for the groups of funds distinguished in terms of the region of a primary investment focus. Source: Author's own study

To sum up this section, coefficients referring to differences in alpha (α) between quantitative and qualitative funds, which were estimated for a whole sample, suggested that quantitative funds were outperformed by qualitative funds in all periods of low weak-form informational efficiency of equity markets. Contrary to expectations, quantitative funds did not manage to take advantage of market inefficiencies in a better way than qualitative funds when considering a whole research sample. The results obtained in the windows related to the global financial crisis (windows ending in 2008 and 2009) are in line with the results obtained in Section 7.6. i.e., in a similar study based on the relative measures of portfolio performance as well as, raw and excess returns. On the other hand, the results obtained in this section for the window ending in 2020 are not in line with the results obtained in Section 7.6.

Regarding the results obtained for different strategies, the most consistent results over all three examined windows were obtained for the group of mixed asset funds, in which quantitative funds were outperformed by qualitative funds and the estimates were statistically significant. In other groups, in the majority of cases, the estimates were statistically insignificant. Quantitative funds appeared to perform better in most cases in the group of absolute return funds. In the case of equity and hedge funds, some clear differences could be observed between the windows related to the global financial crisis (GFC) and the window ending in 2020. In the first two windows, quantitative funds managed better in the group of hedge funds. In the last examined window they managed worse. The opposite was true in the case of equity funds. Such results share some similarities with the results discussed in Section 7.6. The aforementioned similarities are especially relevant to the windows ending in 2008 and 2009. When it comes to the window ending in 2020, the differences are larger. The results obtained for the window ending in 2020 in the groups of equity and hedge funds allow for drawing similar conclusions in both conducted studies.

Moving to differences in alpha (α) between quantitative and qualitative funds in different regions, the most consistent results across all examined windows were obtained in the groups of funds primarily investing in Eastern Asia and Northern Europe. Regarding funds primarily investing in Eastern Asia, quantitative funds performed mostly worse and the results were mostly statistically significant. On the other hand, in the group of funds primarily investing in Northern Europe, quantitative funds performed better; however, the results were mostly statistically insignificant. In the case of funds primarily investing in Northern America and Western Europe, some clear differences could be observed between the windows related to the global financial crisis and the window ending in 2020. In both groups, in the windows related to the GFC, quantitative funds did better. On the other hand, in the window ending in 2020, the opposite was true. The results obtained for the groups of funds primarily investing in Northern America, Northern Europe, and Western Europe share some similarities with the results discussed in Section 7.6. The biggest differences can be observed in the case of the group of funds primarily investing in Eastern Asia, where in the case of the windows related to the global financial crisis, the results suggested the opposite conclusions.

When it comes to differences in market timing between quantitative and qualitative funds, which were estimated for a whole sample, in the windows related to the global financial crisis, quantitative funds had better market timing compared to qualitative funds. On the other hand, in the window ending in 2020, rather, no differences between quantitative and qualitative funds could be observed.

Regarding the results obtained for different strategies, the most consistent results over all three windows were obtained for equity, hedge, and mixed asset funds. In all three examined windows, quantitative funds did better in terms of market timing in the groups of equity and mixed asset funds. However, only in the group of equity funds, the estimates were statistically significant. The opposite was true in the case of hedge funds. As far as quantitative absolute return funds are concerned, they had better market-timing skills than qualitative funds only in the periods related to the GFC. In the window ending in 2020, the opposite was true.

Moving to results obtained for different regions, the most consistent indications over all three windows were obtained in the groups of funds primarily investing in Northern America and Northern Europe. In both groups, quantitative funds had better market timing compared to qualitative funds. In the two remaining groups, quantitative funds did better in this matter only in the periods related to the GFC. In the window ending in 2020 the opposite was true.

8.4. Conclusions

With the use of the modified Capital Asset Pricing Model (CAPM), the modified Treynor-Mazuy model (TM), and a comparative analysis of the results of their estimations, the third part of the study aims to answer four research questions. The first research question is whether the performance of quantitative funds is higher than the performance of qualitative funds. This question strictly relates to the main research hypothesis H1. The second question is whether quantitative funds perform better than qualitative funds in periods of low weak-form informational efficiency of equity markets. The second question strictly relates to the supplementary research hypothesis H3. The other two questions posed are supplementary. The first of them is whether the differences in performance between quantitative and qualitative funds differ between the groups of funds distinguished in terms of strategy and the region of a primary investment focus. The second supplementary question is whether quantitative funds are less exposed to systematic risk than qualitative funds.

In order to reach the research objectives, a special attention has been paid to a comparative analysis of estimated coefficients referring to differences in selectivity and market-timing skills between quantitative and qualitative funds. Such coefficients were added to the classic versions of the applied econometric models. The Beta2 (β_2) coefficient added to a classic CAPM model and standing by $Type_i$ ($\beta_2 Type_i$) informed about the higher (when positive) or lower (when negative) alpha (α) generated by quantitative funds compared to qualitative funds. The same referred to the Beta3 (β_3) coefficient added to a classic TM model. The Beta4 (β_4) coefficient added to a classic TM model and standing by $Type_i(Rm_t - Rf_t)^2$ ($\beta_4 Type_i(Rm_t - Rf_t)^2$) informed about the higher (when positive) or lower (when negative) market-timing skills of quantitative funds compared to qualitative funds. However, despite a special importance of the aforementioned coefficients, the other coefficients of the modified CAPM and TM models were also discussed.

The coefficients informing about the higher or lower alpha (α) generated by quantitative funds compared to qualitative funds (Beta2 (β_2) in the CAPM model and Beta3 (β_3) in the TM model), estimated for all funds together, suggested that in the vast majority of cases, quantitative funds were outperformed by qualitative funds. However, the differences were small and even decreased in the long term. It is worth mentioning that the importance of these conclusions is low, as in the majority of cases, the estimates were statistically insignificant. These results are different from those obtained in Chapter 7 for the overall sample, where in not that substantial majority of cases, quantitative funds outperformed qualitative funds.

When it comes to the TM model estimated for all funds together and the estimates of the Beta4 (β_4) coefficient referring to differences in market-timing skills, quantitative funds turned out to outperform qualitative funds in the vast majority of windows. Nevertheless, in just a few of them, the estimates were statistically significant, diminishing the importance of conclusions drawn.

Differences in selectivity and market-timing skills between quantitative and qualitative funds varied between the groups distinguished in terms of strategy and the region of a primary investment focus. To begin with differences in selectivity skills in the groups distinguished by strategy, in some of the groups like absolute return and hedge funds, quantitative funds outperformed qualitative funds in the vast majority of cases. However, this conclusion should be approached with caution especially in the case of hedge funds, as the percentage of statistically significant estimates was low. In the case of equity funds, the advantage of quantitative funds over qualitative funds pertained to about half of estimates, especially to the most recent ones. It may suggest that quantitative equity funds became more developed over time. On the other hand, in the group of mixed asset funds, quantitative funds were outperformed in almost all windows. Moreover, the estimates obtained for this group were most frequently statistically valid. The results obtained for separate strategies in this section are more similar to the results obtained in Chapter 7 than the results for the overall sample. In Chapter 7, quantitative funds outperformed qualitative funds more frequently in the groups of absolute return, hedge, and equity funds. In the group of mixed asset funds, quantitative funds were outperformed more frequently.

As far as differences in market-timing skills are concerned, the results behaved quite differently in the groups distinguished by strategy. Quantitative funds outperformed qualitative funds in the groups of equity and mixed asset funds in the majority of cases. On the other hand, in the groups of hedge and absolute return funds, for the most part, quantitative funds had worse market timing compared to qualitative funds. It pertained to hedge funds in particular. Nevertheless, these conclusions should be approached with caution, as less than half of the estimates were statistically insignificant. The results pertaining to selectivity and market-timing skills suggest that the selectivity skills of quantitative funds do not necessarily come with market-timing skills. In none of the groups, quantitative funds had a clear advantage over qualitative funds in terms of both selectivity and market-timing skills.

Differences in selectivity skills between quantitative and qualitative funds also varied between the groups distinguished in terms of the region of a primary investment focus, but not as much as in the case of the groups distinguished in terms of strategy. In the groups of funds primarily investing in Eastern Asia and Northern America, quantitative funds outperformed qualitative funds in about half of the windows, especially in the most recent ones. In the group of funds primarily investing in Western Europe, quantitative funds were outperformed a little more often. Nevertheless, such conclusions should be approached with caution, especially in the case of funds primarily investing in Western Europe, as most of their estimated coefficients were statistically insignificant. Much different results were obtained for the group of funds primarily investing in Northern Europe. Quantitative funds from this group outperformed qualitative funds in the substantial majority of windows. However, the percentage of statistically significant windows in this group was especially scarce. Such results allow for drawing slightly different conclusions compared to the results of the study discussed in Chapter 7. Namely, in the study discussed in Chapter 7, quantitative funds were usually more frequently outperformed by qualitative funds across all groups distinguished in terms of the region of a primary investment focus. The opposite was true when considering the TNA-weighted results.

Referring to differences in market-timing skills, the results behaved quite differently in different groups distinguished in terms of the region of a primary investment focus. Quantitative funds outperformed qualitative funds in the majority of windows in the groups of funds primarily investing in Eastern Asia, Northern America, and Northern Europe. Clearly different results can be observed in the group of funds primarily investing in Western Europe, where quantitative funds outperformed qualitative funds in a little less than half of cases. Nevertheless, conclusions pertaining to differences in market-timing skills in the regions should be approached with caution, as in about half of cases they were statistically insignificant. In the case of funds primarily investing in Eastern Asia, this percentage was even lower.

The results obtained in the third part of the study do not unambiguously suggest rejecting the H1 hypothesis, as according to some estimates, there were groups in which quantitative funds provided systematically better performance compared to qualitative funds. However, just in the group of absolute return funds, quantitative funds clearly outperformed qualitative funds. It is worth adding that it did not hold in the case of market-timing skills.

Issue-related studies addressing the problem of the performance of quantitative funds focused especially on hedge funds and their sub-groups (e.g., Chincarini, 2014; Harvey et al., 2017; Chuang and Kuan, 2018). The results of the aforementioned studies suggest that quantitative funds mostly outperformed qualitiative funds in terms of generated alpha. Similar conclusions could be drawn from one of the first issue-related studies, i.e., the one by Parvez and Sudhir (2005), who examined a relatively small sample of enhanced index equity funds. Despite the application of different econometric models, the results obtained in this study (the study conducted for the needs of this thesis) shared some similarities with the results of the studies by Chincarini (2014), Harvey et al. (2017), and Chuang and Kuan (2018). However, they were not fully consistent. On the one hand, quantitative hedge funds examined in this study systematically outperformed qualitative funds in terms of generated alpha (similarly as in the aforementioned studies). But, on the other hand, the results obtained were statistically insignificant in most cases. Thus, the conclusions drawn are not statistically valid. The most similar results to those of Parvez and Sudhir (2005), Chincarini (2014), Harvey et al. (2017), and Chuang and Kuan (2018) were obtained for the groups of absolute return funds and in the most recent windows for equity funds.

Chincarini (2014) also raised the issue of the market-timing skills of quantitative hedge funds. According to the results of his study, quantitative funds turned out to have better market-timing skills than qualitative funds. Such conclusions did not hold in the case of this study, as in the group of hedge funds, quantitative funds turned out to have systematically worse market-timing skills compared to qualitative funds. However, the low rate of statistically significant estimates decreases the value of this conclusion. Statistically significant estimates pertained to the latest windows in particular. According to the results of this study, in the majority of cases, quantitative funds turned out to have higher market-timing skills than qualitative funds in the groups of equity and mixed asset funds.

The study on the performance of quantitative funds in periods of low weak-form informational efficiency of equity markets, which has been discussed in this section, revealed some further differences between quantitative and qualitative funds. Considering the results pertaining to selectivity skills, the results of the study discussed in this section share many similarities with the results of the analogical study discussed in Section 7.6. However, the aforementioned similarities mostly pertained to windows related to the global financial crisis. In most cases, the results obtained for the windows ending in 2008 and 2009 allowed for drawing similar conclusions. When it comes to the results obtained for the window ending in

2020, they did not share many similarities with the results of the analogical study discussed in Section 7.6. In many cases they were also different from the result received for the windows related to the global financial crisis.

The results obtained for the overall sample suggest rejecting the H3 hypothesis. However, the results obtained for separate groups give not so unambiguous indications. Taking into account selectivity skills and groups distinguished in terms of strategy, quantitative funds took advantage of market inefficiencies in a better way compared to qualitative funds in the groups of absolute return and hedge funds. In the other groups, the opposite was true. On the other hand, when taking into account market timing, quantitative funds managed better in the groups of absolute return and especially equity, as well as mixed asset funds. Thus, usually, the advantage of quantitative funds in terms of selectivity skills did not come with the advantage in terms of market timing. Only in the group of absolute return funds, quantitative funds tended to outperform qualitative funds in terms of both examined skills.

When considering groups distinguished in terms of the region of a primary investment focus, the results pertaining to selectivity and market-timing skills were just slightly more consistent. Taking into account selectivity skills, quantitative funds took advantage of market inefficiencies in a better way compared to qualitative funds in the groups of funds primarily investing in Northern and Western Europe. When it comes to market-timing skills, quantitative funds turned out to perform better in all three examined windows. Thus, in the groups of funds primarily investing in Northern and Western Europe, quantitative funds tended to outperform qualitative funds in terms of both examined skills.

The results obtained in the third part of the study do not unambiguously suggest rejecting the H3 hypothesis, as in periods of low weak-form informational efficiency of equity markets, quantitative funds had a clear advantage over qualitative funds in few examined samples, taking into account all discussed performance measures. Quantitative funds were marked by higher performance in terms of market timing in most of the groups, especially in the period related to the global financial crisis. However, when looking at the alpha parameter, the advantage of quantitative funds was not that obvious. Taking into account the results obtained for all discussed performance measures, quantitative funds appeared to take advantage of market inefficiencies in a better way only in the groups of absolute return funds and funds primarily investing in Northern Europe.

As was already mentioned, according to the results of the third part of the study, differences in performance between quantitative and qualitative funds behaved differently among the examined samples. It pertained to groups distinguished in terms of strategy, as well as groups distinguished in terms of the region of a primary investment focus. Differences between the groups distinguished in terms of strategy were much more visible. When considering selectivity skills, the application of quantitative portfolio management techniques was especially beneficial in the case of absolute return and hedge funds. However, when considering market timing, the application of quantitative portfolio management techniques worked in equity and mixed asset funds.

Referring to the supplementary research question of whether quantitative funds are less exposed to systematic risk than qualitative funds, in some of the examined groups, some clear differences between quantitative and qualitative funds in the systematic risk exposure could be observed. Quantitative funds were exposed to a higher systematic risk compared to qualitative funds in the majority of cases in a whole research sample, in the samples of equity and mixed asset funds, as well as in the sample of funds primarily investing in Eastern Asia. The opposite was true in the case of hedge funds, as well as funds primarily investing in Northern America and Western Europe. No substantial differences in terms of systematic risk exposure between quantitative and qualitative funds could be observed in the case of absolute return funds. It is also worth mentioning that the results obtained allowed for stating that the differences in systematic risk between quantitative and qualitative funds differed between the samples examined.

Ending remarks

The foregoing issue-related studies related to quantitative funds and quantitative portfolio management suggest that there are many characteristics that distinguish them from traditionally managed funds and the traditional approach to portfolio management. Differences in the approach to portfolio management between quantitative and qualitative funds may be reflected in differences in their performance. Most empirical studies on the performance of quantitative funds appear to confirm the existence of differences between quantitative and qualitative funds in terms of their performance. In most cases, these differences are in favour of quantitative funds, suggesting that the application of quantitative portfolio management may generate observable benefits when it comes to performance. However, the investigation of the performance of quantitative funds requires additional evidence from more diverse and larger universes of investment funds.

The main objective of this thesis was to evaluate the performance of quantitative funds in relation to the performance of qualitative funds. The study conducted for the needs of this thesis focused on nearly three hundred thousand live and dead investment funds, which operated in years 2000-2020 and were classified as absolute return, equity, hedge, or mixed asset funds according to the Lipper Global Classification scheme. The theoretical part of this thesis began with the review of the definitions of quantitative, qualitative, and hybrid funds. Other concepts closely related to quantitative funds and commonly mentioned in the literature were also discussed. Due to the lack of complete consensus in the reviewed definitions and nomenclature, some general definitions were proposed in order to reconcile the definitions found in the issue-related literature. Then, on the basis of widely accessible industry reports and articles from the financial press, an attempt was made to understand the meaning of quantitative funds and other issue-related concepts to financial markets. Further considerations pertained to the theoretical background for developing the methodology for testing the weak-form informational efficiency of quantitative funds and equity markets. The next theoretical part of this thesis provided some background for developing the methodology for the evaluation of the performance of quantitative funds. A methodological part of this thesis began with the review of the fund classification methods applied in the issue-related studies and the presentation of the fund classification method applied in this study. Further considerations pertained to the methodology of the study on the weak-form informational efficiency and performance of quantitative funds.

The study was divided into three separate parts. An empirical part of this thesis consisted of three separate chapters that referred to each part of the study. The first part of the study was dedicated to weak-form informational efficiency testing and applied martingale difference hypothesis tests, as well as normality test. The second part of the study focused on the examination of the performance of quantitative funds with the use of the relative measures of portfolio performance, as well as raw and excess returns. The third part of the study also focused on the examination of the performance of quantitative funds, but this time, with the use of some classic econometric models, which were modified for the needs of this study. These modifications of the classic models aimed to capture differences in performance between quantitative and qualitative funds. The three parts of the study were based on a comparative analysis, in which the results of quantitative funds were compared with the results of qualitative funds. In the first and second part of the study, the average results for each group of funds were compared.

Conclusions and the verification of research hypotheses

The research hypotheses stated in the introduction were tested in the empirical part of this thesis. The main research hypothesis (H1) states that the performance of quantitative funds is higher than the performance of qualitative funds. This hypothesis was verified in the second and third part of the study. The performance was examined for monthly returns over many rolling windows in the entire research period from 2000 to 2020 for several different samples of investment funds, namely, a whole research sample, four sub-samples distinguished in terms of strategy applied, and four most numerous sub-samples distinguished in terms of the region of a primary investment focus.

When considering the estimates of the coefficient informing about differences in alpha obtained in the third part of the study and the results obtained for the relative measures of portfolio performance in the second part of the study, in the case of a whole research sample, they allowed to draw some inconsistent conclusions. According to the estimates of the coefficient informing about differences in the alpha parameter, quantitative funds were outperformed by qualitative funds most of the time. However, a substantial part of the estimates was statistically insignificant, reducing the validity of this conclusion. On the other hand, according to the results for the relative measures of portfolio performance, quantitative funds outperformed qualitative funds just slightly more often. The results obtained in the second and third part of the study appeared to be more consistent at the level of particular strategies. Quantitative funds turned out to outperform qualitative funds in the majority of cases in the groups of absolute return, equity, and hedge funds. It should be mentioned that quantitative funds had a clear advantage over qualitative funds only in the group of absolute return funds. On the other hand, quantitative funds managed clearly worse in the group of mixed asset funds. The results at the level of individual regions appeared to be more ambiguous compared to the results at the level of individual strategies. Nevertheless, they rather suggest that quantitative funds were outperformed by qualitative funds slightly more often in all groups except for the group of funds primarily investing in Northern Europe. The advantage of qualitative funds was not high. The results of the Northern European group suggest that quantitative funds outperformed qualitative funds slightly more often. However, a certain level of ambiguousness between different measures could also be observed. The least level of ambiguousness could be observed in the group of funds primarily investing in Western Europe, in which qualitative funds slightly more frequently outperformed quantitative funds.

When considering market-timing skills, the results obtained in the third part of the study turned out to be mostly not in line with the estimates of the coefficient informing about differences in the alpha parameter, which referred to selectivity skills. In the case of a whole sample, quantitative funds outperformed qualitative funds in the vast majority of cases in terms of market timing. In the case of selectivity skills, the opposite was true. However, it should be noted that slightly less than half of the estimated coefficients pertaining to market timing were statistically significant. What is more, the advantage of quantitative funds over qualitative funds in terms of market timing tended to decrease over the windows.

At the level of individual strategies, in the great majority of cases, quantitative funds had worse market timing in the groups of absolute return and hedge funds. This may be quite surprising, as in these groups, quantitative funds had a more systematic advantage in terms of selectivity skills. On the other hand, quantitative funds had a more systematic advantage in terms of market timing in the group of mixed asset funds. According to the estimates of the coefficient informing about differences in the alpha parameter and the results obtained in the second part of the study, in the group of mixed asset funds, quantitative funds were outperformed in the vast majority of cases. Quantitative funds also had better market timing in the group of equity funds. In none of the groups distinguished in terms of applied strategy, quantitative funds had a clear advantage over qualitative funds in terms of both selectivity and market-timing skills. The same was true to for groups distinguished in terms of the region of a primary investment focus. When it comes to the examined regions, a more systematic outperformance of qualitative funds by quantitative funds in terms of market timing could be observed in the groups of funds primarily investing in Eastern Asia, Northern America, and Northern Europe. This observation also may be surprising, as quantitative funds in the Eastern Asian and Northern American groups tended to be outperformed in the majority of cases in terms of selectivity skills. More consistent results were obtained for the groups of funds primarily investing in Northern Europe and Western Europe. In the group of funds primarily investing in Western Europe, quantitative funds were outperformed slightly more often in terms of both selectivity and market timing. The opposite was true in the case of the group of funds primarily investing in Northern Europe.

The results obtained in the second and third parts of the study do not unambiguously suggest rejecting the H1 hypothesis, as according to some performance measures, in some examined samples, quantitative funds provided systematically better performance compared to qualitative funds. According to the estimates of the coefficient informing about differences in the alpha parameter and the relative measures of portfolio performance, quantitative funds managed to systematically outperform qualitative funds in the group of hedge funds and in the group of absolute return funds. The advantage of quantitative funds was clear in the case of the latter one in particular. However, the dominance of quantitative funds in the groups of hedge funds and absolute return funds did not hold in the case of market-timing skills. According to estimates of the coefficient informing about differences in the alpha parameter and the parameter related to differences in market-timing skills, quantitative funds managed to gain more systematic advantage over qualitative funds in the group of funds primarily investing in Northern Europe. In terms of market-timing skills, quantitative funds tended to gain more systematic advantage also in the overall sample, in the groups of equity and mixed asset funds, and in the groups of funds primarily investing in Eastern Asia and Northern America. However, it should be noted that the estimates of the parameter pertaining to differences in market timing were statistically significant in the minority of cases.

The second and third part of the study also provided many interesting conclusions, which constituted the answers to supplementary research questions posed in the introduction. Regarding the similarity of quantitative and qualitative funds in terms of the homogeneity of performance they generated, the interquartile range of most relative measures of portfolio performance appeared to be slightly higher in the case of quantitative funds compared to qualitative funds. Almost no differences in spread between quantitative and qualitative funds could be observed in the case of raw and excess returns. The main differences in the spreads between quantitative and qualitative funds turned out to result from the differences in the 75th percentiles. The 75th percentiles appeared to be higher in the case of quantitative funds, suggesting that the upper 25% of observations of the relative measures of portfolio performance in the group of quantitative funds had higher values.

The following supplementary research question pertained to the similarity of quantitative and qualitative funds in terms of the correlation between their raw returns. When considering the results obtained for the entire research sample and all windows, the average Pearson correlation coefficients in the groups of quantitative and qualitative funds appeared to be positive, moderate, and quite similar. In the case of quantitative funds, the average Pearson correlation coefficient was slightly higher, suggesting that quantitative funds were slightly more similar to each other than qualitative funds in terms of the correlation between their raw returns. The average correlation coefficient between quantitative and qualitative funds was very similar to the coefficients mentioned above. The levels of the Pearson correlation coefficient in the examined groups changed substantially over the windows, from being on the verge of positively low and moderate to positively high. The behaviour of the correlation coefficients was similar in the groups of quantitative and qualitative funds.

When taking into account the results obtained between and within the strategies, the results turned out to be strategy-dependent. The lowest results that indicate low and positive correlations could be observed in the groups paired with hedge funds. Only in these groups, the average correlation coefficients of quant funds were lower compared to qualitative funds. Slightly higher correlations could be observed in the groups paired with absolute return funds. The highest correlations could be observed in the groups related to equity and mixed asset funds. Correlations in these groups could be considered moderate. In these groups, the investment funds applied the most similar strategies in terms of the raw returns generated. A common feature of the examined groups was that the differences between the correlations of quant and qual funds were mostly slight. Low correlations in the groups related to hedge and absolute return funds seem to be justified, as funds from these groups are expected to apply varied and sophisticated strategies engaging derivatives and short positions.

In the case of grouping by the region of a primary investment focus, the correlations turned out to be region-dependent. The lowest average correlation coefficients could be observed in the groups paired with the groups of funds primarily investing in the region of Eastern Asia. The highest correlations on the verge of moderate and high could be observed in the case of the group of funds primarily investing in Northern Europe. Slightly lower correlations could be observed in the groups of Northern America and Western Europe. The differences between the correlations among the quant and qual funds were slight.

In the process of the verification of the H1 hypothesis, it turned out that the differences in performance between quantitative and qualitative funds behaved differently among the examined samples. It referred to groups distinguished in terms of strategy, as well as groups distinguished in terms of the region of a primary investment focus. However, the differences between the groups distinguished in terms of strategy were much more visible.

The second part of the study delivered some interesting conclusions related to the connection between the size of quantitative funds and their performance. The results obtained suggest that larger quantitative funds in terms of total net assets (TNA) delivered higher performance than smaller quantitative funds in the majority of cases across almost all examined groups. The larger funds in terms of TNA delivered higher performance also in the group of qualitative funds. However, it did not pertain to such many examined samples as in the case of quantitative funds, and the outperformance of smaller funds by the larger ones was not so clear. In the case of some groups distinguished in terms of the region of a primary investment focus, larger qualitative funds managed even worse. These groups were qualitative funds primarily investing in Northern Europe and Western Europe. A higher positive relationship between TNA and performance in the case of quantitative funds may suggest that the TNA managed has a greater impact on performance in the case of quantitative funds. Larger managed funds may be related to larger expenditures on the development of profitable quantitative portfolio management processes.

Moving to the following important conclusions, the differences between the indications of the relative measures of portfolio performance and raw returns, as well as excess returns, suggest that in most examined groups, quantitative funds were less risky than qualitative funds in terms of risk related to the distribution of returns they generated. It did not pertain to groups of funds primarily investing in Eastern Asia and Northern Europe.

The differences in systematic risk between quantitative and qualitative funds were examined in detail in the third part of the study. The results obtained allow for stating that differences in systematic risk between quantitative and qualitative funds differed between the samples examined. When it comes to groups in which some clear differences could be observed, quantitative funds were exposed to a higher systematic risk compared to qualitative funds in the great majority of cases in a whole research sample, in the samples of equity and mixed asset funds, as well as in the sample of funds primarily investing in Eastern Asia. The opposite was true in the case of hedge funds, as well as in the case of funds primarily investing in Northern America and Western Europe.

Regarding the differences in performance between quantitative funds and their relevant equity market benchmarks, when looking at the results obtained for the relative measures of portfolio performance, in the second part of the study, quantitative funds turned out to clearly systematically outperform the market only in the case of hedge funds. Moreover, the outperformance of the market by quantitative funds, but not that systematic, could be observed in the case of a whole sample, samples of absolute return and equity funds, as well as sample of funds primarily investing in Eastern Asia. On the other hand, the market systematically outperformed quantitative funds in the case of funds primarily investing in the remaining three regions. A not so clear and systematic outperformance of quantitative funds by the market could be observed in the group of mixed asset funds. The abovementioned considerations pertained to the indications of the relative measures of portfolio performance. According to raw and excess returns, quantitative funds were dominated by the market in almost all examined groups. It suggests that the risk related to investment in quantitative funds is much lower compared to investment in a passive equity market portfolio.

The first supplementary research hypothesis, which was verified in this thesis, namely the H2 hypothesis, stated that the weak-form informational efficiency of quantitative funds was higher than the weak-form informational efficiency of qualitative funds. The H2 hypothesis was verified in the first part of the study with the use of the MDH and normality tests. The two groups of applied tests provided quite different results. Nevertheless, drawing some general conclusions was still manageable. When looking at the results obtained for a whole sample over the windows, quantitative funds turned out to be more frequently more efficient compared to qualitative funds. However, the advantage of quantitative funds was not substantially often. At the level of individual groups distinguished in terms of the applied strategy, a similar situation could be observed in the groups of absolute return and equity funds. When it comes to the other two strategies, namely hedge and mixed asset funds, the situation was not so clear, as the results provided by the two types of tests were highly inconsistent. However, according to the more preferable MDH tests, the advantage of quantitative funds in terms of efficiency was clearly more often. Regarding groups distinguished in terms of the region of a primary investment focus, both groups of tests provided results that allowed to draw consistent conclusions only in the case of two groups, i.e., funds primarily investing in Northern America and Northern Europe. In the case of funds primarily investing in Northern America, qualitative funds were more efficient clearly more often. On the other hand, in the case of funds primarily investing in Northern Europe, quantitative funds were more efficient slightly more often. In the other two groups, the results provided by the two groups of tests were highly inconsistent. However, according to the MDH tests, in the group of Eastern Asia, quantitative funds had lower efficiency most of the time. In the case of the group of Western Europe, the opposite was true.

The advantage of quantitative funds over qualitative funds could be observed at the level of a whole sample and individual groups distinguished in terms of the applied strategy. Nevertheless, just in the case of few groups, this advantage was clearly systematic. At the level of individual groups distinguished in terms of the region of a primary investment focus, the situation looked quite different, as in the case of some samples, qualitative funds had more systematic advantage over quantitative funds. Therefore, the results obtained in the first part of the study do not unambiguously suggest the rejection of the H2 hypothesis.

The first part of the study also delivered many interesting conclusions that constituted the answers to supplementary research questions posed in the introduction. The results of the first part of the study suggest that the differences in the weak-form informational efficiency between quantitative and qualitative funds differed between the groups of funds distinguished in terms of strategy and the region of a primary investment focus.

Moreover, according to the results of the first part of the study, larger quantitative funds in terms of TNA turned out to be more frequently more efficient than smaller quantitative funds in almost all the examined groups. The most systematic advantage of larger quantitative funds over the smaller ones could be observed in a whole sample, a sample of equity funds and a sample of funds primarily investing in Northern America. Larger funds in terms of TNA turned out to be more frequently more efficient also in the group of qualitative funds. Nevertheless, a discussed phenomenon was stronger in the case of quantitative funds.

Regarding the differences in informational efficiency between quantitative funds and their relevant equity market benchmarks, quantitative funds did not manage to gain any clear advantage over the market. It pertained to any group examined. Moreover, according to the results of the MDH tests, the efficiency of quantitative funds was lower compared to the efficiency of the markets in the great majority of cases in the groups of absolute return and hedge funds. According to the indications of normality tests, quantitative funds had lower efficiency compared to equity markets in the vast majority of time windows in all examined groups. However, it is worth mentioning that qualitative funds were found to be even slightly worse than quantitative funds in terms of differences in informational efficiency between them and their relevant equity market benchmarks. Differences in informational efficiency between quantitative funds and their relevant equity market benchmarks for the groups distinguished in terms of the region of a primary investment focus were not examined due to the small number of markets in each region.

The window ending in 2009 was indicated as the window of the lowest levels of equity market efficiency by the results of the MDH tests. The windows ending in 2008 and 2020 were indicated as the windows of the lowest levels of equity market efficiency by the results of normality tests. Regarding the differences in efficiency between quantitative and qualitative funds in periods of low efficiency of equity markets, when comparing the results obtained for the non-weighted fund categories, none of the applied tests suggested any significant differences between quantitative and qualitative funds. However, when taking into account the TNA-weighted categories, larger funds turned out to be less efficient, especially in the quant fund group. However, this observation was not confirmed by the indication of the automatic Portmanteau test. Therefore, the results suggest that in periods of the lowest levels of equity market efficiency, some substantial differences in efficiency between quantitative and qualitative funds were observable after accounting for TNA. The larger funds in terms of TNA were less efficient in the groups of quantitative and qualitative funds. However, especially larger quantitative funds were worse in this matter.

A supplementary research hypothesis H3 states that quantitative funds perform better than qualitative funds in periods of low weak-form informational efficiency of equity markets. The same as in the case of the H1 hypothesis, the H3 hypothesis was verified in the second and third part of the study. When considering the estimates of the coefficient informing about differences in the alpha parameter obtained in the third part of the study and the results obtained for the relative measures of portfolio performance in the second part of the study, they allowed to draw quite similar conclusions, especially in the period related to the global financial crisis. When looking at a whole research sample, quantitative funds appeared to take advantage of market inefficiencies in a worse way compared to qualitative funds. At the level of individual strategies, quantitative funds seemed to do mostly better in the group of absolute return funds. The opposite was true in the case of equity and mixed asset funds. In the case of the hedge fund group, the results were inconsistent. Regarding the groups distinguished in terms of the region of a primary investment focus, a clear outperformance of quantitative funds by qualitative funds could be observed in the groups of funds primarily investing in Eastern Asia and Northern America. On the other hand, quantitative funds performed better in the group of Northern Europe. As far as a group of Western Europe is concerned, it is difficult to make any general conclusions, as the results obtained in both parts of the study were too inconsistent.

Moving to differences in market timing between quantitative and qualitative funds in periods of low weak-form informational efficiency of equity markets, in the overall sample, quantitative funds turned out to outperform qualitative funds in the period related to the global financial crisis. In the window ending in 2020, the opposite was true. At the level of individual groups distinguished in terms of the applied strategy and the region of a primary investment focus, quantitative funds usually outperformed qualitative funds. Nevertheless, a group of hedge funds was a clear exception. In the group of hedge funds, quantitative funds had worse market-timing skills compared to qualitative funds.

The results obtained in the second and third part of the study do not unambiguously suggest rejecting the H3 hypothesis, as according to some performance measures, in some examined samples, quantitative funds provided a better performance in periods of low weak-form informational efficiency of equity markets compared to qualitative funds. Quantitative funds were marked by higher performance in terms of market timing in most of the groups and especially in the period related to the global financial crisis. Nevertheless, when looking at the alpha parameter and the relative measures of portfolio performance, the advantage of quantitative funds was not that obvious. Taking into account the results obtained for all discussed performance measures, quantitative funds appeared to take advantage of market inefficiencies in a better way only in the groups of absolute return funds and funds primarily investing in Northern Europe.

Discussion

In most cases, the foregoing issue-related studies addressing the problem of the performance of quantitative funds were dedicated to one group of investment funds, such as equity or hedge funds. Not all groups of funds examined in this study were covered in the previous issue-related studies. Thus, it is difficult to fully discuss the results of the study conducted for the needs of this thesis with other issue-related studies. Such studies like those by Chincarini (2014), Harvey et al. (2017), and Chuang and Kuan (2018) focused on hedge funds retrieved from the Hedge Fund Research (HFR) database. The results obtained in these studies allowed to draw partially similar conclusions to those drawn from the results obtained for hedge funds in the study conducted for the needs of this thesis. Similarly as in the case of the aforementioned studies, the results obtained in this study suggest that quantitative hedge funds mostly outperformed qualitative hedge funds in terms of generated alpha. However, it should be remembered that the studies discussed applied different models. The advantage of quantitative funds resulting from the estimates of econometric models obtained in this study also appeared to be confirmed by the indications of the relative measures of portfolio performance. However, the estimates of the coefficients that inform about differences in generated alphas obtained in this study for hedge funds turned out to be statistically insignificant in the majority of cases. Taking into account generated alphas and the relative measures of portfolio performance, in the case of the study conducted for the needs of this thesis, the clearest differences between quantitative and qualitative funds in favour of quantitative funds could be observed in the case of absolute return funds. On the other hand, the clearest differences between quantitative and qualitative funds in favour of qualitative funds could be observed in the case of mixed asset funds. It is also worth adding that the indications of the numerous relative measures of portfolio performance were similar. It was in line with the studies by Eling and Schuhmacher (2007), Eling (2008), Ornelas, Silva, and Fernandes (2012), as well as Zakamouline (2010), who proposed that different relative measures of portfolio performance allowed to develop similar rankings of investment funds.

The differences in market timing between quantitative and qualitative funds examined by Chincarini (2014) in the study on the sample of hedge funds suggested that quantitative funds performed better in this matter. The results of the study by Chincarini (2014) were not in line with the results of the study conducted for the needs of this thesis, as in the group of hedge funds, quantitative funds appeared to be mostly outperformed by qualitative funds in terms of market-timing skills. A clear advantage of quantitative funds over qualitative funds in terms of market-timing skills could be observed in the case of the groups of equity and mixed asset funds.

The advantage of quantitative funds over qualitative funds was also found in a relatively small sample of enhanced index equity funds examined by Parvez and Sudhir (2005) in one of the first issue-related studies addressing the issue of differences in performance between quantitative and qualitative funds. It seems difficult to compare the results of the study by Parvez and Sudhir (2005) with the results of the study conducted for the needs of this thesis, as the methodology of the study conducted for the needs of this thesis did not distinguish a sample of enhanced index equity funds. Moreover, the documentation of the Lipper Global Classification applied in this study does not distinguish the universe of enhanced index equity funds and does not provide any information on whether this group of funds is included in the database. If the results of the study by Parvez and Sudhir (2005) were compared with the results obtained for the group of equity funds in the study conducted for the needs of this thesis, there would be another issue, namely, a small size of the sample applied by Parvez and Sudhir (2005) that might result in a limited power of tests. This limitation was also indicated by Parvez and Sudhir (2005). However, as opposed to the results of the study by Parvez and Sudhir (2005), the results obtained in the study conducted for the needs of this thesis for equity funds did not suggest a clear advantage of quantitative funds.

Following Harvey et al. (2017), this study aimed to answer supplementary research questions pertaining to the similarity of quantitative and qualitative funds in terms of the homogeneity of performance they generated and in terms of the correlation between their raw returns. Regarding the homogeneity of performance, the findings of the study conducted for the needs of this thesis slightly deviated from the findings of Harvey et al. (2017), who proposed that in general, systematic and discretionary funds (as they called them) were similar in terms of the homogeneity of performance generated. According to the results of the study conducted for the needs of this thesis, the spread of the majority of the relative measures of portfolio performance appeared to be slightly higher in the case of quantitative funds. The main differences in the interquartile range between quantitative and qualitative funds turned out to result from the differences in the 75th percentiles.

In order to verify common beliefs that systematic funds were highly homogenous and highly correlated due to the similarities of their strategies, Harvey et al. (2017) examined the correlations between the performance of systematic and discretionary funds. According to the results of Harvey et al. (2017), the correlations between the performance of systematic and discretionary funds appeared to be high and positive, suggesting that systematic and discretionary funds were quite similar in terms of performance generated and the common beliefs were unjustified. The results of the study conduced for the needs of this thesis are quite different. The correlation between the raw returns of quantitative and qualitative funds in the group of hedge funds turned out to be positive and low, suggesting that quantitative and qualitative funds are not that similar in terms of performance generated. It was one of the lowest results among all the examined groups. Results similar to those obtained by Harvey et al. (2017) could be observed in the groups of equity and mixed asset funds.

Moderate correlations between quantitative and qualitative funds obtained in this study in the group of equity funds were not in line with the results presented in the reports by AQR (2017), Lakonishok and Swaminathan (2010), and Lin (2019), who examined active equity funds retrieved from the eVestment database. According to the results obtained by these researchers, the correlations within the groups of quantitative and qualitative funds were positive, low, and similar. When it comes to the results obtained in the study conducted for the needs of this thesis, similar results could be observed in the group of hedge funds.

According to Harvey et al. (2017), who examined the universe of hedge funds, the exposure to risk factors was higher in the case of discretionary managers. Such results are in line with the results obtained in this study, as in the group of hedge funds, quantitative funds were less exposed to systematic risk in the majority of cases. On the other hand, the results obtained in this study for equity funds are not in line with the results of the study by Abis (2018), who focused on US equity mutual funds. According to Abis (2018), quantitative funds had better risk management and portfolio diversification throughout the business cycle. The results obtained in the study conducted for the needs of this thesis suggest that in the group of equity funds, quantitative funds were exposed to a higher systematic risk in most cases.

The results of the MDH and normality tests in the study on the weak-form informational efficiency unambiguously suggested that the period related to the GFC was marked by the lowest levels of the weak-form efficiency. Especially in the groups of equity and mixed asset funds in the period related to the GFC, quantitative funds turned out to be outperformed by qualitative funds. Such results are in line with the conclusions proposed by Abis (2018). According to Chincarini (2014), who examined a sample of hedge funds retrieved from the HFR database, quantitative funds had higher alphas during the GFC. Such results also appear to be in line with the results obtained in the study conducted for the needs of this thesis, as in the group of hedge funds, quantitative funds appeared to mostly outperform qualitative funds. However, it should be noted that the estimates obtained were statistically insignificant.

A common decrease in the informational efficiency of equity markets up to the window ending in 2009, which was indicated by the results of the first part of the study, was most likely related to the global financial crisis 2007-2008. This conclusion would be in line with the studies by Horta et al. (2014), Sensoy and Tabak (2015), Anagnostidis et al. (2016), as well as Mensi et al. (2017). They suggested that the global financial crisis negatively affected the weak-form informational efficiency of equity markets. On the other hand, Katris and Daskalaki (2013), as well as Singh, Deepak, and Kumar (2015) proposed that the global financial crisis had no significant impact on the weak-form informational efficiency of equity markets. The results of the first part of the study also suggested that the efficiency of quantitative and qualitative funds followed the efficiency of the markets, indicating that their efficiency behaved similarly. According to normality tests, after the post-crisis recovery, the efficiency started to decrease across the markets and funds again in the following windows, reaching the lowest levels in the window ending in 2020. There is a possibility that this plunge could be related to the coronavirus outbreak. It would be in line with the studies by Dias, Heliodoro, Alexandre, and Silva (2020), Dias et al. (2020), as well as Lalwani and Meshram (2020). However, this decrease began in the windows preceding the coronavirus outbreak and was not indicated by more reliable MDH tests.

Taking into account alpha and the relative measures of portfolio performance, quantitative funds outperformed qualitative funds in periods of low informational efficiency of the market in just few examined groups. As opposed to the assumptions of Parvez and Sudhir (2005), quantitative funds mostly did not take advantage of market inefficiencies in a better way than qualitative funds. The situation looked different in the case of market timing. When considering market timing, quantitative funds were better than qualitative funds in the majority of examined samples.

Limitations and future directions for studies

Data pertaining to investment funds retrieved from the Thomson Reuters Eikon database allowed to collect a relatively large research sample compared to other studies raising the issue of the performance of quantitaive funds. The method of the classification of investment funds applied in this study was similar to the method applied by Harvey et al. (2017). However, the share of quantitative funds in their research samples was much higher. They applied a different database, namely the Hedge Fund Research (HFR) database. High differences in the share of quantitative funds between the aforementioned study and the study conducted for the needs of this thesis may suggest that the fund objective description in Thomson Reuters Eikon database could have been insufficient and inaccurate to distinguish quantitative funds properly. However, the results of the studies by Chincarini (2014) and Harvey et al. (2017), which used the HFR database, share some similarities with the results of the study conducted for the needs of this thesis. Furthermore, the results of the study by Chuang and Kuan (2018) also share some similarities with the results of the study conducted for the needs of this thesis. They also utilized the HFR database, but applied a much different method of classification of investment funds. Future studies addressing the issue of the performance of quantitative funds may apply some different databases in order to find out whether their selection allows to draw conclusions similar to those obtained in the foregoing studies.

Future studies addressing the problem of the performance of quantitative funds may also focus on developing more and more robust methods of classification of investment funds. This study applied a method similar to the one proposed by Harvey et al. (2017). A possible bias resulting from the application of different split methods was first emphasized by Chincarini (2014). In further studies, the researchers tried to come up with less and less subjective split methods. For instance, Abis (2018), as well as Chuang and Kuan (2018) applied more sophisticated methods based on machine learning. Thus, the following issue-related studies can focus on finding more robust and more objective methods for distinguishing quantitative funds in financial databases.

The study conducted for the needs of this thesis focused on testing just one form of informational efficiency, namely the weak one. Future studies can examine quantitative funds also in terms of the other forms of informational efficiency, such as the semi-strong and strong form. Another limitation of this study pertains to considering just one risk factor in applied econometric models, namely the equity market benchmark, which constitutes a systematic risk factor. It was some kind of compromise between the size and diversity of the research sample and the number of considered risk factors. Collecting and processing such a large sample of investment funds constituted a huge challenge, especially in terms of technical aspects. Collecting other risk factors would constitute another great challenge. In addition, in many cases, it would be impossible due to the lack of access to relevant databases.

Contribution and applications

This study aimed to contribute to the body of knowledge related to the evaluation of the performance of quantitative funds not only by presenting a different approach to the evaluation of the performance of quantitative funds, but also by introducing some theoretical considerations pertaining to the issue-related definitions and nomenclature proposed in the foregoing studies. In the light of the lack of complete consensus among researchers on the nomenclature and formulation of definitions, this study proposed the universal definitions of quantitative, qualitative, and hybrid funds that aimed to reflect their substance in the best way possible. The results of theoretical considerations highlighted significant differences between quantitative and qualitative funds and led to the proposal of the most important criterion that separates quantitative funds from qualitative funds. This criterion is the answer to the question: "Does the investment fund apply a predefined and automated investment process?". Further considerations taking into account market data presented in widely accessible industry reports indicated that indisputably, quantitative funds, as well as related phenomena, such as quantitative and algorithmic trading, are very important to financial markets and their importance still increases.

Regarding empirical considerations, this thesis aimed to contribute to the body of knowledge pertaining to the evaluation of the performance of quantitative funds by introducing a comprehensive study employing a relatively large sample and covering a relatively long research period compared to the foregoing issue-related studies. The study conducted for the needs of this thesis examined the performance of quantitative funds included in four numerous groups distinguished in terms of the strategy applied. The empirical study was also conducted at the level of individual groups of funds distinguished in terms of the region of a primary investment focus. What is more, this thesis aimed to fill the research gap by connecting the study on the performance of quantitative funds with the study on the features of the returns of quantitative funds in the context of the weak-form informational efficiency. The application of the rolling window method aimed to capture changes in the performance and efficiency of quantitative funds. The further contribution of this thesis may be related to the study on the performance of quantitative funds in periods of low weak-form efficiency of equity markets, which aimed to verify the validity of a belief shared in the issue-related literature that quantitative funds make use of market inefficiencies in a better way than qualitative funds.

The study conducted for the needs of this thesis may be useful especially to portfolio managers who consider the implementation of quantitative portfolio management techniques. It may also be useful to investors wondering whether quantitative funds have an advantage over classic approaches to portfolio management in terms of generated performance. Market regulators interested in the operations of quantitative funds, which apply predefined and automated investment processes, may learn about their profitability and risk to investors, weak-form efficiency, and the behaviour of their performance and weak-form efficiency in periods of the instability of equity markets. Furthermore, this study may constitute a motivation to providers of financial databases to implement the next classification of investment fund that indicates whether a given fund is quantitative.

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