CORVINUS UNIVERSITY OF BUDAPEST

# ANOMALIES AROUND REPORTS OF STOCK EARNINGS AND OF FUND MANAGEMENT

DOCTORAL DISSERTATION

Supervisor: Csóka, Péter PhD and Pintér, Miklós PhD

Rácz, Dávid Andor

Budapest, 2019

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DOCTORAL SCHOOL OF BUSINESS AND MANAGEMENT

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## Aknowledgments

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*„Who does not count, does not matter.”*

*András Prékopa*

# 1. LITERATURE AND METHODOLOGY SUMMARY

In the financial markets there are many abnormalities and market failures. Two of these are analysed in the dissertation, which are connected by a logical clamp that, by knowing and appropriately managing both, investors can avoid inefficiencies that reduce investors' utility as they lead to suboptimal decisions, missed profits or avoidable losses and ultimately lead to high levels of social costs.

One of the anomalies analysed around the period of quarterly reports of exchange listed companies is a question of market efficiency, which can be analysed by the presence of abnormal returns. This pricing anomaly is relevant for the investor because if in the period before and after the earning reports the abnormal returns show typical mispricing trends the investor would like to recognize them in order to increase his own utility by taking advantage through trading of the existing arbitrage-like opportunities, whereby the mispricing would cease and the market pricing would return to its real and effective value. Alone the aggregate market capitalization of exchange listed companies constituting the S&P 500 is about 22 trillion U.S. dollars[1], so the potentially affected wealth by this market failures is enormous in size worldwide.

After reviewing the literature on market efficiency and presenting the methodology of event study in chapter 2.1. summarizing our calculations, we will search the answer to the question (1) whether the direction and magnitude of EPS surprises in the quarterly reports of S&P 500 index shares determines the price reactions, and what is the interval at which abnormal returns occur. A further question is (2) whether in case of stock market companies that operate in the technology sector and that have a more uncertain assessment due to greater vagueness, the experienced abnormal exchange reactions outweigh that of companies belonging to the general stock market.

According to our results the direction and magnitude of surprise in companies' profitability determines how stock prices change due to company reports. At the same

[1] http://siblisresearch.com/data/total-market-cap-sp-500/

time, there is a shift in the level and direction of the cumulative abnormal yields observed for each news groups to negative price reactions, as a significant positive yield is only seen in the very good news group. The impact of the new information on the post-notification trading days is no longer observed and no trend develops in the direction of surprise. Thus, the analysis confirms that the market for shares in the selected sample is moderately efficient. Generally, significantly greater price reactions can be seen in the news groups of the S&P 500 IT index than in the news groups of the S&P 500 index.

The other anomaly analysed in the dissertation is experienced in assessing the performance of investment funds in the manipulation of performance measures, through which investment fund managers can improve their performance without real added value in order to attract more investors and capital. However, it should be noted that activity called performance manipulation by the literature is in vast majority of cases is not an illegal act or fraud, but rather a misleading activity. In doing so, the investment fund manager knowingly or unconsciously conducts an investment activity that increases only the value of classic performance measures (and indirectly his own commission), but not the utility of the rational investor (although the mystified investor suffering from behavioural distortion might rejoice), and thus it constitutes of suboptimal investment decisions. Ingersoll et al. (2007) demonstrated that well-constructed performance measures starting from a utility-based approach can be used to eliminate the problems arising from the manipulation of classic performance measures. Their value can only be increased by investment decisions where the investment manager has additional information relative to the market or is able to create real added value by the possession of his timing and selection capability.

There are basically two types of performance manipulation: one is return smoothing, when by the creative assessment of illiquid or hard-to-evaluate assets the fund manager tries to smooth out possible loss periods and thus artificially reduces the standard deviation and thereby increases the detected risk-adjusted performance. This type of activity in the Hungarian market can practically be ruled out, as a separate and independent custodian assesses and publishes the net asset value of the units of the funds daily in general. The other method is the topic of dynamic manipulation, where the investment fund manager makes its investment strategy conditional on its recent performance and not merely on a rational analysis of the market situation. For example, he flees into risk-free assets to the remainder of the year to protect the return premium compared to the benchmark that has already been achieved in the first part of the year. However, the problem with this activity is that it can lead to suboptimal investment decisions that, while protecting or improving detected performance, are damaging to investors because they do not increase investor utility and skip promising investment opportunities due to exaggerated risk avoidance.

Market failures resulting from performance manipulation can cause serious, social-scale damage, as investment decisions based on manipulated returns and performance measures will be sub-optimal, i.e. investment market participants will not allocate capital to the investments funds, in which they would have invested, if they invested not based on the manipulated and misleading classical measures but on the basis of real performance. Thus, in the end, capital does not flow through investment funds to companies which could have performed the most efficient, most value-added investments from the inflow of funds, thus missed profit occurs on a social level and valuable investments are cancelled. Further research in the field of social utility are the funds that have great utility from an environmental, social and governance perspective (On issues of the financial returns of energy efficiency investments look at Rácz (2012)). Only in the US 16 trillion dollars of assets are found in the management of actively managed investment funds about[2].

Market inefficiencies will also occur if return manipulation cannot be filtered out in performance evaluation, then not those fund managers will get adequate premiums, who are able to create real added value, but those market participants who are successful in performance manipulation.

In the literature review we overview the evolution of the performance evaluation of investment funds, then we move over to the introduction of Manipulation Proof Performance Measures (MPPM). We evade to the MPPM based Doubt Ratio as a

[2] https://seekingalpha.com/article/4213088-lipper-u-s-mutual-funds-etps-q3-2018-snapshot

manipulation detecting measure, and also to alternative return manipulation detecting ways, to the Doubt Ratio and to the discontinuity analysis. Involving our own calculations in chapter 2.2 we are looking for the traces of return manipulation or sub-optimal investments decisions in our analysis made on Hungarian absolute return funds data, which is a new result as no example is yet known in the literature on detecting the traces of return manipulation in case of Hungarian investment funds.

According to our results, the rank correlation between the MPPM and Sharpe ratios is in the 0.76 - 0.82 range, which indicates a level of difference compared to the classic measures that can be caused by some level of return manipulation or return smoothing. As a new result we conclude, that in opposition to expectation according to the literature, the linear approximation of the MPPM by Brown et al. (2010) is less punishing on risk than the Ingersoll et al. (2007) calculus and so it is sometimes inaccurate in an extent that even influences the ranking compared to the original Ingersoll et al. (2007) formula. Therefore, the calculation of MPPM as a new finding is recommended using the Ingersoll et al. (2007) method.

Another new result is that, according to our own calculations, although the Doubt Ratio was built by Brown et al (2010), however it is rewarding to use the version based on the Ingersoll et al. (2007) MPPM as inaccuracies occurring in the MPPM are generally inherited to the Doubt Ratio

Another new result of our calculations contributing to the literature is that, in contrast to the close overlap of the Doubted Ratio with alternative return manipulation detecting methods observed in the literature (based on Brown et al. (2010) 80% match), the results of our analysed sample were mixed: The alternative methods reported potential anomalies from the 31 investment funds in 10 cases, i.e. some yield manipulation or suboptimal investment decisions were most likely, whereas the Doubt Ratio only identified 4 investment funds as suspicions. In case of the former, the confirmation by the discontinuity analysis is in 4 out of 10 cases, while in case of Doubt Ratio it is only confirmed 1 out of 4.

Overall, according to our results, the Bias Ratio has proved to be a better pre-screening tool for more detailed analysis of return manipulation (e.g. with discontinuity analysis) than the Doubt Ratio. Based on investment policies and interviews with investment managers, only in case of one fund, the Concorde Citadella fund could the simultaneous suspicious signals on return manipulation or suboptimal investment decisions given by several methods be considered as justified, and this fund was marked as suspicious by both the Doubt Ratio and the Bias Ratio. In the case of this fund, the existence of distortion due to sometimes sub-optimal investment decisions seems well founded in the knowledge of investment policy.

A new approach was also taken when a graphical representation of clear deviations from the group average was used to segregate suspicious investment funds, both in terms of the Doubt Ratio and the Bias Ratio. based on our own calculations we recommend using the following protocol to filter performance manipulation: 1. The discontinuity analysis of investment funds with a Doubt Ratio of more than 150, and the assessment of the Bias Ratio according to the median rule. 2. A graphical representation of the values of the Bias Ratio and Doubt Ratio in the Bias Ratio-Doubt Ratio space and, subsequently based on the deviation from the group average, the discontinuity analysis of the returns of investment funds that appear to be outliers. 3. discontinuity analysis of investment funds with Bias Ratios higher than the median. 4. An overview of investment policies to understand the underlying investment decisions that can strengthen or refute the potential existence of suboptimal decisions, or weaken the reliability of statistical methods, for example if the composition of the investment fund is overweighed with fixed-income assets, or when the fund operates as fund of funds and always allocates the vast majority of its capital into investment funds.

The structure of the dissertation is the following: In chapter 1. the literature and methodology summary can be found, within it in chapter 1.1. the theories and critiques of market efficiency are summarised first. It is followed by the methodology of event study in chapter 1.2. In chapter 1.3. the evolution of investment funds' performance assessment and also the manipulation proof performance measures and performance manipulation detecting methods are presented. In chapter 2. we move to the discussion of our own results, so in chapter 2.1. we analyse the price effects of quarterly reports by executing a hypothesis analysis on market efficiency and on the question if there is a significant difference in the extent of abnormal returns in case of S&P500 and S&P 500

IT. Following this in chapter 2.2. we look for the traces of performance manipulation or sub-optimal investment decisions in case of Hungarian absolute return funds by comparing the rankings of classic measures with the ranking of MPPM, moreover by using the Doubt Ratio and other alternative manipulation detecting methods. In chapter 3 we finish the dissertation by concluding our results.

## 1.1. THEORY AND CRITIQUES OF MARKET EFFICIENCY

This chapter is summarising the literature of market efficiency and its discussion is based on our working paper Rácz and Huszár (2018), and also on our publication Rácz and Huszár (2019, pp. 244-246.). The equilibrium price on the market of a financial product can be interpreted as the combined opinion of market participants on the value of the product, based on all the information available to them at the time. Market prices change according to the information market participants have and according to the image they form about this information; every piece of news and information that changes the perceived value of a given product on the market has an effect on supply and demand, and, as a result, on the equilibrium price of the product.

The effect that information has on prices is perhaps the most conspicuous on the stock markets. Strict disclosure regulations apply to listed companies, which means these companies are much more transparent than others. The literature on the effect of new information on share prices is extensive due to the good observability of the phenomenon. Seminal studies by Ball and Brown (1968), and Fama, et al. (1969) introduced the methodology of event study that is essentially the same as that which is in use today (MacKinlay, 1997).

The main aim of the early studies mentioned was to provide empirical confirmation for the efficient market hypothesis (Fama, 1970). These results – and additional studies by many researchers – supported the assumption, and as a result the efficient market theory became an integral and dominant part of financial thinking. However, over time, criticism appeared in literature, mostly from experts of behavioural finance. According to this theory investor psychology and cognitive biases should be taken into account. Numerous studies that describe the connection between investor psychology and asset pricing empirically weaken the validity of the efficient market hypothesis (see Hirshleifer (2001), Barberis and Thaler (2003)).

### 1.1.1. The efficient market theory and the random walk of share prices

This sub-chapter is summarising the literature of efficient market theory. The value of any security equals the present value of its future cash flows, and in a perfect world this is the equilibrium price as well. In the case of stocks, it is the present value of future dividends (For dividend patterns and the pricing of stocks see e.g. Havran et al. (2015)). As we have no comprehensive information about these future cash flows, share prices reflect the expectations of investors. However, the fundamentals, the revenue-generating ability and thus the valuation of a company change as a result of market shocks and individual shocks. This process is described by the efficient market theory.

A market in which prices always fully reflect available information is called efficient (Fama, 1970). Share prices follow a random walk (or rather a random walk with drift since expected return can be non-zero), which implies that returns are unpredictable from past returns, and the best forecast of a return is its historical mean. On an efficient market, above-average risk-weighted returns are due to chance alone and are not sustainable in the long term. This also implies that no arbitrage opportunities exist, as prices adjust to all new information without delay (Fama, 1970; Fama, 1991; Malkiel, 2005).

We can differentiate three forms of market efficiency – weak, semi-strong, strong. According to the weak form of the theory future returns cannot be forecasted from data of the past. According to the moderate form all publicly available information are already built in the price. While in case of the strong form not only information accessible publicly, but all information is built into the market prices (Fama, 1970).

Grossman and Stiglitz (1980) pointed out that costless information is a necessary condition for efficiency as it was originally defined. Otherwise, if we applied the weak form of the condition, it wouldn’t be in the interest of investors to obtain costly information, as they would receive no compensation in a market with no arbitrage opportunities. Nevertheless, if information is inexpensive, the market price will reveal most of the informed traders’ information. One example is the time when quarterly reports are disclosed: accurate information becomes available to wide audiences, which temporarily increases the liquidity of the shares (Váradi et al., 2012). Whenever we refer to advocates of efficiency later, we refer to this more loosely interpreted hypothesis.

### 1.1.2. Critiques of efficient markets and test of the semi-strong form of efficient market

This subchapter summarises the literature of the critics and tests of the efficient market. In addition to the effect of new information, share prices are also influenced by other factors, by several elements of psychology that Akerlof and Shiller (2011) call animal spirit.

The theoretical framework the most closely related to our research questions is the semi-strong form tests of market efficiency. These event studies examine how share prices react when new information becomes available. On an efficient market, *a surprise shock should be almost immediately and fully reflected* in the market price. There is, however, extensive literature on cases when this does not happen. Possible reasons fall into two categories basically; it is either that price response is delayed, or that certain risk premiums are not included in the pricing model, so we may detect abnormal returns with it (Bernard & Thomas, 1989).

In addition to the continuation of short term returns, Fama and French (1996), and Fama (1998) mention another important anomaly, the momentum after corporate reports, i.e. the share price trend, which is a series of price changes in the same direction over a longer period and which cannot be explained in the three-factor model either.

Chan, et al. (1996) mentions two possible behavioural patterns that may cause postearnings- announcement momentum. One is that due to the market's underreaction, prices adjust to new information slower. Another possibility is that 'trend-chasers' reinforce movements in stock prices even in the absence of fundamental information. Behavioural models are built on both explanations (Barberis, et al. (1998), Daniel, et al. (1998)).

Several researches mention that the effect of various cognitive biases is more significant in case of illiquid stocks (Chordia et al. (2009), Chordia et al. (2014)), and when there is more uncertainty regarding the valuation of a company (Daniel & Titman (1999), Hirshleifer (2001), Kumar (2009)). The research of Zhang (2006) and Francis et al. (2007) substantiates that price reaction to surprise news is slower in case of growth stocks where there is more uncertainty about the firm's value.

### 1.1.3. Behavioural economics background of anomalies

This subchapter presents the behavioural economics background of anomalies affecting experienced market efficiency. Based on the anomalies described in the previous subchapter, a clear question emerges of how psychological effects prevail in price movements. Akerlof and Shiller (2011) argue that experienced often extreme price movements are impossible to be explained only by fundamental causes and are merely attributed to rational behaviour.

Malkiel (2003), Danielsson et al. (2009) and Soros (2003, pp. 49-72), says that not only the changes in fundamentals and real risks, but also the risks *perceived* by investors affect investors' behaviour and thus the market price. With a low perceived risk, the willingness to take risks increases, which can also increase the leverage and thus the swings in prices (Berlinger, et al., 2012).

According to the prospect theory of Kahneman and Tversky (1979) (or its enhanced version of the cumulative prospect theory-Kahneman and Tversky, 1992) we generally inaccurately estimate probabilities: We will overestimate the occurrence of events with extremely small probabilities. Based on Kahneman and Tversky (1979), the modified value function is not symmetrical: our utility is generally reduced to a greater extent in the same amount of losses than in the case of gains. This may explain why fear of loss can cause serious price drops under the influence of negative news.

The representativeness (representativeness heuristic) described by Kahneman and Tversky may also be responsible for the excessive price response: In estimating probability, not the overall distribution is taken into account by investors, but returns that are closer in time are overvalued, and are considered a representative sample and causality is assumed behind the random clustering of yields (Kahneman (2013), Kahneman and Riepe (1998), Hirschleifer (2001). A related distortion overconfidence: People overestimate the accuracy of their own estimates and are able to trust their own information and analysis even against public announcements, than to take into account the error of their own analyses (Kahneman & Riepe, 1998). The self-attribution bias is a phenomenon further strengthening this: the lucky outcomes are attributed to their own abilities, while the opposite events are considered noises. All of these distortions may be liable to overreactions and subsequent in prices (Daniel and Tito (1999), Daniel et al. (2001)).

However, there are also behavioural distortions opposing these effects, such as conservatism (Barberis et al. (1998)): when new information is considered by investors as a transitional, one-off effect, so that it is not or not fully reflected in the price, and only if the actors see a trend in the new information line, the price responds to changes in full. Chan, et al. (1996) considers that this is due to the slow-changing analysts' estimations, as their projections strongly influence market participants. According to Brown, et al. (2013), large institutional investors take into account analytical forecasts, and their actions can lead to a herding and to extreme price swings.

Limited or shared attention (the impact of other notifications that are not linked to a particular share) can also cause modest exchange rates, which may result in a slow reaction. Hou et al (2009), Hirschleifer (2009), deHaan, et al. (2015) observe that managers try to report bad news after exchange closure or on busy days when fewer attention can be paid to them. Similar empirical observation is that the managers as far as they can, try to conceal from the public the unpleasant news and losses, as noted by Berlinger et al. (2018).

Fama (1998) says that the theory of efficient markets provides a better general explanation than the behavioural economics approach. However, the findings of alternative theories should be taken into account as they provide useful insights and theoretical bases for a number of phenomena.

### 1.1.4. Market efficiency and the existence of arbitrage returns

In this subchapter, we are referring to the question based on the literature whether the existence of market efficiency is equal to the observation that the vast majority of market participants are not capable of realising persistently arbitrage returns. Despite the results of behavioural economics, it is an open question that if the yields can be predicted at some level due to irrational price reactions, is it possible to achieve lasting and significant premiums in relation to market returns. However, passive portfolios are often able to overperform active portfolio management because of the high transaction costs that are typical for the latter. (Malkiel, 2005)

Although several examples and investors are known to be able to overperform market returns with an active investment style (Schwager, 2012a; Schwager, 2012b), but these cases and actors are relatively rare, the rarely upcoming arbitrage-opportunities are not entirely risk-free and generally disappear soon after their recognition. (Daniel & Titman, 1999; Malkiel, 2003)

However, the lack of arbitrage opportunities and the level of prices close to fair value are not equivalent. While correct pricing implies arbitrage freedom and market efficiency, the fact that participants are generally not finding arbitrage- opportunities does not lead to market efficiency and that the market is correctly evaluating the real fundaments in prices (Barberis & Thaler, 2003). However, rare examples of the most successful investors prove that the arbitrage-opportunities due to mispricing is not common and difficult to exploit. However, as market participants are neither perfectly informed nor free from behavioural distortions described by behavioural economics, it can be explained why prices and price trends may persist far from the real fundamentals even to a longer period of time.

### 1.1.5. Testing of market efficiency with the methodology of event studies

A number of examples of the analysis of market efficiency with the methodology of the event studies can be found in the literature. Among these are a mix of those that show significant or insignificant abnormal returns during the periods around company reports:

Watts (1978) examines the impact of the quarterly reports searching for the significant presence of cumulative abnormal returns of 73 NYSE companies in the periods around their 75 quarterly reports and showed significant abnormal yields, although their extent did not exceed the trading costs. Foster et al. (1984) examined the existence of a trend following 56 000 quarterly company reports between 1974 and 1981 through abnormal returns, and found a mixed result: the existence of the trend was not always significant.

Pellicer and Rees (1999) investigated the impact of the 660 company reports between 1991 and 1995 in Spain and found significant abnormal returns, volatility and beta growth. Skinner and Sloan (2002) examined the presence of abnormal returns around 103 274 quarterly reports between 1984 and 1996, and concluded that growth-shares are more sensitive to negative news than value-type shares. Mallikarjunappa and Dsouza (2014) investigated the 30-30-day period around quarterly reports in December 2011 of 185 companies from the Indian Exchange (Bombay Stock Exchange (BSE)) and detected significant abnormal yields. The analysis we carry out in turn will increase the range of significant abnormal yields detected.

## 1.2. THE METHODOLOGY OF EVENT STUDIES

In this chapter we summarise the methodology of event studies based on the literature. This analysis tool is being applied in many scientific fields for the last couple of decades and its role in empirical finances cannot be doubt. The methodology used for the analysis of the research questions is the event study. When describing the methodology, we mostly rely on studies by MacKinlay (1997), Binder (1998), Kothari and Warner (2007) and Corrado (2011), which discuss this analysis procedure extensively. Based on this we describe the procedure of the event study, and the methodology details that are the most important for our research. in the description of the methodology, we use the notations of MacKinlay (1997). The discussion in the chapter is based on our working paper Rácz and Huszár (2018), and also on our publication Rácz and Huszár (2019, pp. 247-251.).

### Steps of the procedure

In finance, the question we examine is the price response of certain securities to some economic event. More precisely, we want to know if there is abnormal return as a result of the given event.

The initial task is to define the event of interest and the related event window, the period around the event over which prices will be examined. This is followed by the selection of the sample according to various selection criteria. After that we define how we will measure abnormal return. This is expressed by the following equation:

$$AR_{i\tau} = R_{i\tau} - E(R_{i\tau}|X_{\tau}) \quad , \qquad (1)$$

where $AR_{i\tau}$ is the abnormal return for security i for time period $\tau$, $R_{i\tau}$ is the actual realised return, and, $E(R_{i\tau}|X_{i\tau})$ is the expected return. $X_{\tau}$ is the conditioning information for the expected model, and it is determined by the available information and the asset pricing model used (MacKinlay, 1997; Kothari & Warner, 2007; Corrado, 2011).

### 1.2.1. Modelling of the expected returns

This chapter summarises the modelling steps of expected returns based on the literature. When calculating expected returns, we assume that the returns used for modelling are normal and are independently and identically distributed through time. According to MacKinlay (1997), the majority of event studies use two models: the constant mean return model and the market model. The constant mean return model is often considered naive in literature, as it does not differentiate between the effects of company-specific and market-specific information on share prices (Cable & Holland, 1999; Corrado, 2011). As a result, it is difficult to establish whether the abnormal returns observed are caused by the event examined or by market swings.

The market model provides a more sophisticated solution: like the CAPM-model (Capital Asset Pricing Model; sharpe,1964; Lintner, 1965), it relates the return of any given security to the return of the market portfolio, thus reducing the variance of abnormal return and making the quantification of event effects more precise (MacKinlay, 1997; Corrado, 2011):

$$R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it} \,, \tag{2}$$

$$\varepsilon_{it} \sim N\left(0, \sigma_{\varepsilon_i}^2\right) ,$$

where $R_{it}$ and $R_{mt}$ are the period *t* returns on security *i* and the market portfolio, and $\alpha_i$ and $\beta_i$ are the parameters to be estimated from the regression model. Coefficient $\beta_i$ shows the sensitivity of security *i* to the market portfolio, $\alpha_i$ is the fitting parameter, and $\varepsilon_{it}$ is the error term of the security over period *t*. We assume that the expected value of the error term is zero and has a normal distribution with a variance of $\sigma_{\varepsilon_i}^2$.

In the modelling logic we use, it is assumed that the regression coefficients are constant during the estimation period and in the event window (Binder, 1998). The actual beta of a given stock may change over time. However, examining a short-term horizon, it is unlikely that significant changes occur in risk profiles.

Several methods can be used to model expected returns, like the multifactor models, but the explanatory power of additional factors are usually marginal compared to the market model (MacKinlay, 1997). According to (MacKinlay, 1997), and Cable and Holland (1999) tests indicate that the market model outperforms the CAPM. However, both models are less accurate in estimating actual abnormal returns than multifactor models (e.g. Fama and French 1996). in a large sample, bias averages out to zero, so the market model is efficient for estimating returns (Binder, 1998), and additional factors add little explanatory power (MacKinlay, 1997). Considering all the above, we use the market model hereinafter for calculating normal returns.

### 1.2.2. Length of the event window and the estimation window

In this subchapter we summarise considerations on how long event window and estimation window to use according to the literature to the execution of the analysis. Choice of these is somewhat arbitrary, basically we define the periods based on the experiences of previous researches. The length of the event window and of the estimation window is set somewhat arbitrarily, we fundamentally rely on the experiences of previous studies. The issue we examine is considered short-horizon in an event study, which means a relatively short event window is suitable for testing the hypotheses. The analysis is quite reliable when the event window is shorter than one year, and there are significantly fewer methodological problems in the course of the analysis (Kothari & Warner, 2007).

In our case, the event window must contain the date of the event and at least the following trading day so that announcements made at the end of the trading day or after the closing of the stock exchange are considered too, as in such cases the abnormal return is necessarily detectable the following day, too. This effect is especially significant when the announcement contains bad news for investors (deHaan, et al., 2015; Doyle & Magilke, 2015). in practice, the event window is usually an interval of a few weeks, symmetrically around the event date (MacKinlay, 1997).

The more reduced the size of the event window, the less likely it is that there are impacts of other confounding events pertaining to the companies (Rao & Sreejith, 2014). in our case, economically significant abnormal returns linked to corporate reports can only be expected in a period of a few days around the event. We can also see in the article by

MacKinlay (1997) that a few days after the disclosure of the report, abnormal returns fluctuate around their expected value, i.e. zero. Thus, a window of four weeks seems an appropriate choice.

It is important to consider that if the event window is too long as compared to the estimation window, it can significantly bias the test statistics if estimated abnormal returns are correlated. However, when the event window is 5 days long and the estimation window is 100 days long, the uncorrected test statistic is expected to exceed the corrected one by 1.6 per cent (Binder, 1998). Because of this, we use a period that is longer than MacKinlay's (1997) 120 days, for example a two-year (500 trading day) period to calculate regression coefficients, as suggested by Corrado (2011). it is important to separate the two windows in time; if we used also the return data from the event window for the regression model, the estimation of the parameters would be incorrect as it would also include the noise caused by the announcement (Boehmer, et al., 1991; MacKinlay, 1997; Binder, 1998; Kothari & Warner, 2007).

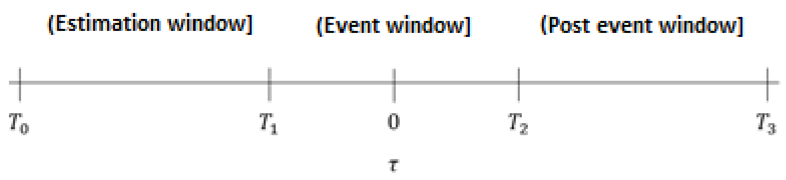


**Figure 1.: Timeline of an event study (MacKinlay, 1997, p. 20).**

In view of the above, the timeline of the event study can be formally put as follows. The running index of returns is $\tau$, and the stages of the study are: $\tau = 0$ is the date of the event, $T_0 + 1 \leq \tau \leq T_1$ is the estimation window, and $T_1 + 1 \leq \tau \leq T_2$ is the event window. in this case $L_1 = T_1 - T_0$ is the length of the estimation window, and $L_2 = T_2 - T_1$ is the length of the event window (see Figure 1). A post-event window can also be defined as $T_2 + 1 \leq \tau \leq T_3$, with a length of $L_3 = T_3 - T_2$, but it is unnecessary for our research questions.

### 1.2.3. Measuring and testing abnormal returns

This subchapter summarises the question on measuring and testing of abnormal returns based on the literature. After selecting the method to model the expected rate (which is a linear function of the rate of the market portfolio), using equations (1) and (2) we can provide a more accurate definition of abnormal return as used in the present article:

$$AR_{i\tau} = R_{i\tau} - E(R_{i\tau}|R_{m\tau}) \quad , \qquad (3)$$

where $T_1 + 1 \leq \tau \leq T_2$, thus $\tau$ represents a period in an event window. The length of the period used for parameter estimation and the period around the event are defined, so we can start building the regression model. the ordinary least squares method (OLS) is used for parameter estimation. We know the expected return calculated during modelling from (2), and substituting this to equation (3) we can calculate the abnormal returns around the event as follows:

$$AR_{i\tau} = R_{i\tau} - (\hat{\alpha}_i + \hat{\beta}_i R_{m\tau}) \quad , \qquad (4)$$

where $AR_{i\tau}$ is the abnormal return of security *i* , $R_{i\tau}$ and $R_{m\tau}$ are the returns of security *i* and the market portfolio over period $\tau$ . $\hat{\beta}_i$ is the estimated regression coefficient for the sensitivity to market return and $\hat{\alpha}_i$ is the fitting parameter.

To be able to draw statistically and economically relevant conclusions regarding the research questions, abnormal returns must be aggregated. Aggregation can be done across the elements of the sample or through time. The first part of our first hypothesis says that as a result of the announcement, share price changes in the same direction as the surprise in the EPS. This assumption can be tested if we aggregate the abnormal returns in the sample that occur when corporate reports are disclosed, based on whether the surprise is positive, negative or neutral. Based on MacKinlay (1997), Binder (1998), Serra (2004), and Kothari and Warner (2007), the average abnormal return in period τ ($\overline{AR}_\tau$) is the arithmetic mean calculated from the data of the elements of the groups:

$$\overline{AR}_\tau = \sum_{i=1}^{N} \frac{AR_{i\tau}}{N} \quad , \qquad (5)$$

where $N$ is the sample size (the number of elements in the group), i.e. the number of events observed. if the value of $L_1$ is high, the variance is (see MacKinlay (1997, p. 21) equation (8)):

$$var(\overline{AR}_\tau) = \frac{1}{N^2}\sum_{i=1}^{N} \sigma_{\varepsilon_i}^2 \quad . \tag{6}$$

A relatively long estimation period is necessary because equation (6) is true if abnormal returns are independent through time. According to MacKinlay (1997) this is true if the size of the sample we use for estimating returns is large enough. As $\sigma_{\varepsilon_i}^2$ is not known, we need to use an estimate for this when variance is calculated. Based on MacKinlay (1997) and Binder (1998) the variance of the error term in equation (2) is a good choice for the calculation, and it can be written as the function of $L_1 = T_1 - T_0$, i.e. the length of the estimation window as follows:

$$\hat{\sigma}_{\varepsilon_i}^2 = \frac{1}{L_1 - 2}\sum_{\tau=T_0+1}^{T_1} \left(R_{i\tau} - \hat{\alpha}_i - \hat{\beta}_i R_{m\tau}\right)^2 \quad . \tag{7}$$

After that the null hypothesis, i.e. that the distribution of $\overline{AR}_\tau$ is normal with an expected value of zero can be tested, thus

$$\overline{AR}_\tau \sim N[0, var(\overline{AR}_\tau)] \quad . \tag{8}$$

It is important to note that to test the statistical significance of the average abnormal return we assume that in time period $\tau$ the $AR_{i\tau}$ abnormal returns of specific observations are independent and have the same distribution. MacKinlay (1997) and Binder (1998) note that cross-sectional data are often correlated. However, this does not cause a problem for the estimation if the event windows of the specific observations do not overlap. Otherwise we cannot assume that the estimated abnormal returns of the sample elements are independent, and in this case, due to their non-zero covariance, the variance estimate is downward biased, and test statistic is upward biased. According to Binder (1998), this bias effect is negligible if the securities are chosen from different industries and the market model is used. Rao and Sreejith (2014) explain that when event periods are randomly dispersed, it helps avoid bias.

If we want to test both the surprise effects of corporate reports and market efficiency, we need to analyse a period longer than the interval consisting of the day of the announcement, and – in case of reports disclosed late in the day or on a non-trading day – the following trading day. This is described in the second part of the first hypothesis. Based on empirical results referenced earlier, we can assume that due to the surprise in the results of the companies, we could detect the momentum effect in share prices in the short term.

To be able to test this assumption, we need to aggregate abnormal returns in the event window through time. Consider an interval between $\tau_1$ and $\tau_2$ for which $T_1 < \tau_1 \leq \tau_2 \leq T_2$. Let cumulative abnormal return (CAR) of security i over this interval be

$$CAR_i(\tau_1, \tau_2) = \sum_{\tau=\tau_1}^{\tau_2} AR_{i\tau} \quad . \tag{9}$$

If we perform the same for the average abnormal returns calculated for the sample and the specific elements of the groups in the sample, we get the cumulative average abnormal returns for any $(\tau_1, \tau_2)$ interval of the event window.

$$\overline{CAR}(\tau_1, \tau_2) = \sum_{\tau=\tau_1}^{\tau_2} \overline{AR}_\tau \quad , \tag{10}$$

$$var\left(\overline{CAR}(\tau_1, \tau_2)\right) = \sum_{\tau=\tau_1}^{\tau_2} var(\overline{AR}_\tau) \quad , \tag{11}$$

where $\overline{AR}_\tau$ and $var(\overline{AR}_\tau)$ are known from (5) and (6) equations (MacKinlay, 1997; Binder, 1998).

Based on this, we can test the null hypothesis: does the cumulative average abnormal return follow a normal distribution with an expected value of zero:

$$\overline{CAR}(\tau_1, \tau_2) \sim N\left[0, var\left(\overline{CAR}(\tau_1, \tau_2)\right)\right] \quad , \tag{12}$$

Or, in normalised form

$$\theta = \frac{\overline{CAR}(\tau_1, \tau_2)}{\sqrt{var\left(\overline{CAR}(\tau_1, \tau_2)\right)}} \sim N(0,1) \quad . \tag{13}$$

With this, we have provided an overview of the main points of the methodology used. We will do the same with the second hypothesis, but there we also examine whether the results from the two samples are significantly different and whether their cumulative average abnormal returns follow a distribution with the same expected value and variance.

## 1.3. LITERATURE OF INVESTMENT FUNDS' PERFORMANCE EVALUATION

This chapter provides an overview of the literature, the characteristics and evolution of the various measures of the performance assessment of investment funds, as well as the issues of performance manipulation and the measures that enables protection against it, and with the help of their application, the possibilities of detecting return manipulation and further alternative methods of detecting return manipulation. The discussion in this chapter is largely based on the description in Rácz (2019a).

Before placing savings in investment funds, the investor must decide from which investment fund to expect to be able to perform in the future according to his return expectation and risk bearing willingness. We do not have complete certainty about the future, and we can only start from past performance and behaviour to form our expectations. In the case of actively managed investment funds, the management of our savings is entrusted to an investment management, so in this case we can only build our expectations based on the past behaviour of the respective investment fund.

As the investment fund manager is also aware of the fact that we are trying to conclude on the future expected performance of the investment fund from the funds' past performance that he manages, therefore it is possible to improve the appearance of his own performance, or to achieve better performance within a given framework, whether with conscious or unconscious investment strategies, which while increase the value of the used measures, but these still might be sub-optimal in terms of investor utility, and therefore the literature calls them performance manipulation. The investment fund manager seeks to achieve increase in the attractiveness of the investment fund it manages and so to attract as many new funds as possible, which leads to higher realized commissions in his hands sooner or later. Zawadowski (2017) presents a disappointing correlation in investment fund managers' focus on commission, because according to his results, the fund managers who demand a higher commission cannot generate more excess return than that in exchange: on the contrary, 1 percentage point higher fees are coupled with over 1 percentage point lower performance on average (Jensen's alpha) compared to the benchmark rate.

Besides relatively rigorous audit activity and independent custodian activity, the possibilities for investment fund managers to be able to manipulate their performance in an artificial and significantly influential way on reality by knowing the measures used for their performance must be very limited. However, it is apparent from the literature that it is not only possible by the flexible assessment of the net asset value of some of their illiquid assets and/or by reporting losses smoothed out, but also through various suboptimal and/or dynamic investment decisions in time to increase the values of the measures used for performance evaluation, while their real performance does not have real improvements (Ingersoll et al. (2007)).

The assessment of actively managed portfolios and so of absolute return funds can be approached from several aspects: Amihud et al. (2015) analyse the effect of the pricing of illiquidity and founds that the sensitivity (beta) to the IML-factor (to the return of the portfolio consisting of illiquid minus liquid shares) is significant in times of increasing financing difficulties, Gemmill et al. (2006) assess British investment funds with the loss-averse performance measure (LAP), that is based on prospect theory, and concludes that the ranking is different to classical measures. Walter (2002) shows that the careless use of a limit and premium system, which takes into account the downside risks fitting the investor's preferences, can develop an extreme investment strategy that no longer complies with the original investors' intentions. When examining fair risk allocation, Csóka and Pintér (2016) acknowledge and Balog et al. (2017) clarify that there is no risk allocation method that is always applicable, stable and motivating at the same time. There is ample literature on measuring the returns and risks of investment funds as well as identifying the factors that influence fund performance.

The further development of performance measures has managed to remedy some of the problems with earlier solutions, but the evaluation of absolute return funds the absence of a benchmark index causes a serious problem. One possible solution to this problem is the calculation of a modified version of the Information Ratio with the use of factors that represent different investment styles (Pojarliev and Levich (2013)). However, the use of required factors is difficult for these investment funds. Furthermore, it is a problem to be tackled, that regarding the measures spread in the literature and currently used by the market the question of manipulability still exist, which is a phenomenon not only affecting absolute return funds, but all investment funds and hedge funds. There are several approaches in the literature to overcome the problem that aim to introduce such performance evaluation measures, which can correctly evaluate risk-return combinations even if the return distributions of investment funds are abnormal, or the possibility of return smoothing or manipulation arises (Ingersoll et al. (2007)).

A possible solution for the problem to use of manipulation-proof performance measures (MPPM), which are based on utility theory weel-known from microeconomics. These measures are especially suitable for the evaluation of actively managed funds as increasing the value of the measure is only possible if the fund manager has real information or ability. In opposite it is impossible by only possessing the information on what kind of measure the market or the evaluator is using the assess performance. This special property describes the Manipulation Proof Performance Measures (MPPMs) against classic measures, which can be manipulated without any surplus knowledge or information, simply by knowing the measure. We demonstrate the criteria to be met by the manipulation proof performance measures and how Ingersoll et al. (2007) identified a possible solution to the problem, how the measure defined by them looks like, which by its structure is suitable to assess the performance of absolute return funds and hedge funds.

We evade to the Brown et al. (2010) approach, which is a linear approximation of the Ingersoll et al. formula and which Brown et al. has presented as a simpler, more easily calculated formula. With the help of the Brown et al approach, Brown et al. was able to better structure the measure in the form of return premium and additional standard deviation, with the help of which the measure was used to evaluate the implied risk aversion. The resulting new indicator was named Doubt Ratio, which may indicate the presence of return smoothing or performance manipulation in case of extreme values.

To conclude the chapter, we introduce those additional alternative techniques and indicators, such as the Bias Ratio and the discontinuity analysis, which inferred from the specificities of the return distribution and/or the distribution of returns around 0 potentially existing return smoothing or other manipulation (Abdulali (2006), Bollen and Pool (2009).

### 1.3.1. The definition of absolute return investments funds

Absolute return investment funds are actively managed and, unlike other investment funds, do not follow benchmarks or indices, but have set themselves the objective to gain a positive return in all market conditions accompanied with low volatility. This is possible, firstly, by incorporating more sophisticated financial products, such as derivatives into their portfolios and thus protect themselves from the risk of losses, while at the same time are able to generate higher yields. On the other hand, the fund manager not only receives a free hand by not obliged to follow a predefined index in all market conditions, but also can decide more freely about the ratio of individual asset classes and investments within the portfolio, contrary to traditional investment funds where the minimum and maximum ratios are prescribed, so that even if the fund manager considers that the market conditions would require, he may not lower the proportion of a given asset class, and thus he cannot avoid certain losses, even if he would be able to do so on the basis of his professional assessment.

### 1.3.2. Classic performance measures

This subsection provides an overview of the c*lassic* performance measures occurring in literature and applications, introducing the structure, the logic used to build them, and how each variant what kind of faults of the predecessors tried to tackle and that in the case of actively managed funds, and in particular of absolute return funds, what gaps occur, which is why we should turn to the search for alternative measures.

**Sharpe-ratio**

The Sharpe-ratio was named after William Sharp (Sharpe, 1966). Originally intended, this indicator is used to determine the optimum ratio of risk-free and risky portfolio elements and measures the premium for additional risk taken. The higher the value of the indicator, the higher the level of the premium per unit risk.

The Sharpe-ratio is the following:

$$S = \frac{R_p - R_f}{\sigma_p} \quad ,$$

where $R_p$ is the return of the investment fund/portfolio, $R_f$ risk-free rate and $\sigma_p$ standard deviation of the investment fund/portfolio.

If the Sharpe-ratio is used for performance assessment, then it "only" explains whether an investment fund provides adequate excess return for one unit of excess risk taken, but it does not show if there is a relationship between the benchmark and the investment fund's performance, and if there is, what kind of relationship it is. In other words the Sharpe-ratio does not break down investment fund performance into the performance arising from the change in the market/benchmark and the performance arising from the individual decisions of the investment fund manager, which stems from the fact, that the fund manager does not always follow passively the benchmark, but makes different investment decisions or different portfolio weights compared to it. This is a problem because classic actively managed funds follow an index or a specific proportion of indexes, in line with the markets covered by the fund, and the fund manager wants to prove his/her skill, competence (and his remuneration is largely dependent on it), whether he is capable of generating an additional benefit in relation to the index (indices) chosen as benchmark by overweighting those investment targets relative to the benchmark, which he values as overperforming targets relative to market indices based on his analyses. Compared to market indices. Therefore, using the Sharpe-ratio we do not possess information, how exactly the fund manager was able to underperform or outperform the benchmark.

### Modifications of the Sharpe ratio

The **Sortino-ratio** (Sortino and Prince, 1994) is one of the modifications of the Sharpe-ratio, which, instead of the total standard deviation, takes into account only the standard deviation of losses, but not the standard deviation of profits. Thus, the Sortino-ratio only considers the standard deviation of losses to be obstacles to overcome and to be risks, but not the standard deviation of profits, as they are overall useful for investors, even if they involve uncertainty.

$$Sortino - rate = \frac{R_p - R_f}{\sigma_d} \quad ,$$

where $R_p$ the return of the investment fund/portfolio, $R_f$ risk-free rate, and $\sigma_d$ the standard deviation of *losses* of the investment fund/portfolio.

The **Calmar-ratio** (Young, 1991) compares the excess return to the highest loss of the examined period (maximum drawdown) instead of standard deviation. Thus, the Sortino-ratio is similar to the Sortino-ratio that it also compares the returns to downside risks, but instead of downside standard deviation, it calculates with the highest experienced loss:

$$Calmar - rate = \frac{R_p - R_f}{Max\ Drawdown} \quad ,$$

where $R_p$ the return of the investment fund/portfolio, $R_f$ risk-free rate, and Max Drawdown, measures the biggest experienced loss during the observed time interval.

Although the Sortino- and Calmar-ratios may more accurately capture risk by quantifying downside risks than the Sharpe-ratio, they do not explain either how the investment fund manager was able to underperform or outperform the benchmark.

**Jensen’s alpha**

The Jensen’s alpha assessment approach was written down 3 years later after the Sharpe-ratio by Michael C. Jensen (Jensen, 1949). Jensen’s alpha quantifies the exact excess return which can be achieved by applying a strategy which is cannot be explained with the current and known explanatory variables/factors. The $\beta_i$ the sensitivity of each investment asset to the return premium of the market portfolio. Thus, as long as the return calculated with the help of $\beta_i$ is determined risk adjusted, the Jensen’s alpha measures purely excess return, but does not quantifies the additional risk taken in relation to the market portfolio/benchmark, and does not adjust with it either:

$$\alpha = R_p - \left[R_f + \sum_i \beta_i \left(R_m - R_f\right)\right] ,$$

where $R_p$ is the return of the investment fund/portfolio, $R_f$ risk-free rate, $\beta_i$ The sensitivity of individual investment assets to the excess return of the market portfolio, finally $\alpha$ the surplus of the investment fund/portfolio which cannot be explained with the help of $\beta_i$-s.

In the literature, Jensen’s alpha is one of the most widely used indicators, as it clearly shows the under-/overperformance/return premium compared to the benchmark index/indices, and its calculation is relatively simple. However, its disadvantage is that it only shows the return the fund manager achieved relative to the benchmark, but it does not say anything about the additional risk the investment manager has bore to achieve this, i.e. how much riskier the portfolio compared to the benchmark is.

**Information Ratio**

One way to measure the extra risk taken is to divide the Jensen's alpha with the standard deviation of the Jensen's alpha and thus obtain the Information Ratio (IR) that Treynor and Black introduced in 1973 (Treynor and Black, 1973). The Information Ratio shows the return premium that the fund manager has reached on one unit of actively taken risk.

$$IR = \frac{\alpha}{\sigma_\alpha} \ ,$$

where $\alpha$ is the return of the investment fund/portfolio, $\sigma_\alpha$ is the standard deviation of $\alpha$.

The information ratio is basically the modification of the Sharpe ratio that instead of the risk-free rate, the excess return relative to the benchmark is compared to the additional risk taken relative to the benchmark index. Similarly to the Jensen's alpha, it gives easy-to-interpret results and is relatively simple to calculate.

The information rate is easy to measure in cases where the benchmark has already been given, such as for ETFs following market indices (Exchange Traded Funds). But in case of absolute return funds, it is not obvious what the benchmark index is, compared to which we can have a correct performance assessment, as these investment funds do not follow clear and well-defined indices or indexes. Instead, their aim is to achieve a positive return accompanied with low volatility in all market conditions.

### 1.3.3. Alpha Ratio

This subchapter presents from the non-classic and not yet widespread performance measures the Alpha Ratio and its application in case of the evaluation of absolute return funds. For these investment funds, according to market practice the benchmark is either a risk-free return or a specific index of government bonds, and the investment manager makes a commitment to overperform this. At the same time, this approach mixes the returns resulting from the Beta and the Jensen's alpha. This is because, although the benchmark is a risk-free rate, part of the yield of the investment fund or portfolio is tied to the Beta, since the fund manager also invests in risky assets, which move along through Betas with certain market indices. Thus, it is inappropriate to derive the Jensen's Alpha from the risk-free return as a benchmark, because a significant portion of the Alphas detected is not actually explained by the knowledge or competence of the fund manager, but rather, that the portfolio composition chosen by him is following a risky index or indices. For this reason, identifying the part of the return of the investment fund or portfolio associated with the relevant benchmark is not a self-evident task, therefore, the calculation of the Information Ratio should be amended. In the followings we will present the new measure, the Alpha Ratio and its practical application in the literature, which can be used to correctly assess absolute return investment funds.

**Alpha Ratio**

One possible solution to overcome the previously described problems is the use of a frame built on risk factors. These factors can display different investment styles or different risk factors. Pojarliev and Levich in their 2013 publication (Pojarliev and Levich, 2013) call the modified Information Ratio as Alpha Ratio (IR*):

$$\text{Alpha Ratio} = \text{IR}^* = \frac{\hat{\alpha}}{\sigma_{\hat{\alpha}}} \quad ,$$

where

$$\hat{\alpha} = R_p - \sum_i \hat{\beta}_{it} F_{it} + e_t \quad ,$$

moreover, $R_p$ is the return of the investment fund/portfolio, $F_{it}$ is the return of the different risk factors/investment styles, $\beta_{it}$ the sensitivity of the return of the investment fund/portfolio to the different risk factors.

Pojarliev and Levich (2013) show an example on the calculation of the Aplha Ratio by applying data from the Deutsche Bank dbSelect database concerning the period 2005-2010. On the dbSelect platform, at Deutsche Bank there are managed investment accounts that allow investors to invest in portfolios of various foreign exchange traders. According to Deutsche in dbSelect around billion USD amount was held by pension funds, fund of funds, private banks, insurance companies and other investors based on August 2013 data.

Pojarliev and Levich (2013) showed how to break down the performance of different foreign exchange traders into Beta and Alpha returns. The earnings of professional forex traders on the dbSelect platform and risk factors ($F_{it}$) have been used that embody popular trading strategies and styles.

Popular strategies are the followings:

1. Carry trade or forward rate bias: This strategy is based on the overall trend that currencies with higher interest rates are generally will be appreciated.
2. Strategies following technical trends: These strategies are based on the lasting movements of the exchange rates.
3. Value-based investment strategies: These strategies are based on long-term average-returning purchase power parity exchange rates.

These strategies are represented by indices as factors that enable investments into different exchange rates in the analysis by Pojarliev and Levich (2013) to calculate the Alpha Ratio. They also use the volatility of the currency market as a fourth explanatory factor:

1. Substitute for the carry trade factor is the Deutsche Bank G10 Harvest Index. The yield of this tradable index is produced as a return on the following investment strategy: A long investment in three of the largest currencies in the G10 foreign exchange universe and, at the same time, the yield from shorting the three low-yield currencies.
2. The trend tracking factor is the AFX Currency Management Index. This index follows the yield of the investment strategy, which consists of investing in seven currency pairs, where investment weights are determined by the spot market trading volume and the rule of three different lengths moving averages.
3. The value-based risk factor is replaced by the Deusche Bank FX PPP Index. Deutsche Bank prepares a ranking as the ratio of the average daily spot rate of

the last three months and the purchase power parity exchange rate published yearly by the OECD. The FX PPP Index reflects the yield that results from the long investment in the three highest-ranking currencies based on Deutsche Bank ranking in the G10 foreign exchange universe, and the short-selling of the three lowest-ranking currencies.

4. The volatility factor does not reflect the yield of a tradable strategy. The authors use the Deutsche Bank Currency Volatility Index as a substitute for the volatility of the currency markets. This index is the three-month weighted average of the implied volatility of nine major currency pairs, where the weights are provided by the trading volumes of the BIS surveys.

| | Excess retrun (%) | Alpha (%) | Carry Beta | Trend Beta | Value Beta | Standard deviation Beta | R squared | IR | Alfa Rate |
|---|---|---|---|---|---|---|---|---|---|
| L27 | 4.15 | 2.92<br>(1.00) | 1.01<br>(**3.41**) | 0.70<br>(**2.56**) | –0.15<br>(–0.68) | –0.06<br>(–0.22) | 0.212 | 0.47 | 0.38 |
| L28 | 4.97 | 4.87<br>(**3.01**) | –0.14<br>(–0.89) | 0.08<br>(0.56) | 0.25<br>(**1.99**) | –0.18<br>(–1.00) | 0.068 | 1.13 | 1.15 |

Data: 87 monthly observation from January 2006 and March 2013. In brackets are the t-values, bold signals statistically significant results on a 5% confidence interval.

**Table 1: Alpha and Beta returns in case of two foreign exchange investors based on Pojarliev and Levich, 2013 p. 100.**

Both manager L27 and L28 has achieved approximately similar annualized excess returns on the 7-year observation period (Jensen's alpha L27: 4.15%, L28: 4.97%). The Information Ratios however show materiel differences: L27: 0.47 and L28: 1.13, which is due to materially higher volatility of manager L27, which deteriorates the return on risk. Since bonuses are based on excess return, both managers would get comparably same premiums.

The analysis makes it clear that the returns of manager L27 can be explained by the carry and trend risk factors. If we take into account the exposures to these factors, then the estimated Alpha of manager L27 drops below 3%, and its value will not be statistically significant either. In opposite manager L28 will have a small but significant exposure to the value factor, which is represented by Deutsche Bank FX PPP Index. The Alpha of manager L28 is 4.87%, which is almost completely the same as his total excess return. Results suggest that manager L28 is able to produce higher excess return by following a strategy that is not represented by the 4 analysed risk factors.

Pojarliev and Levich (2013) calculate in the last column the value of the Alpha Ratio, where beta exposures are first subtracted from the values of the total excess return, thus specifying the Alpha values more accurately and calculating the modified Information Ratio they have defined. Both the traditional Information Ratio and the alternative Alpha Ratio lead to the same conclusion in the authors' analysis: the L28 manager overperforms the L27 Manager.

Pojarliev and Levich (2008) analysed the performance of 34 investment fund that invest in foreign currency, using the same technique. As a substitute for carry trade factor, Citibank's Beta1 G10 Carry Index, to replace the trend tracking factor the AFX Currency Management index was used. The value factor substitute was the Citibank Beta1 Purchasing Power Parity Index, while the substitute for volatility was the one-month implied volatility in EUR/USD and USD/JPY rates.

The average and median values for the Alpha Ratio are smaller than for the traditional Information Ratio. Pojarliev and Levich (2008) in their analysis found eight foreign exchange dealers in the 34-capita sample, whose information rate was positive while the alpha rate was negative. These results show that the results of these foreign exchange dealers can be explained by using the three risk factors analyzed and it is not the result of the managers’ talent.

| Fund manager | Yearly Average Return | Yearly Excess Retrun | Standard deviation | *IR* | Yearly Alpha | Tracking error | *IR** |
|---|---|---|---|---|---|---|---|
| M1 | 22.0% | 19.34% | 14.71% | 1.31 | 22.13 | 14.57% | 1.52 |
| M2 | 6.4 | 3.70 | 8.62 | 0.74 | –2.48 | 4.81 | **–0.52** |
| M3 | 2.5 | –0.16 | 3.00 | –0.05 | 0.31 | 2.94 | 0.11 |
| M4 | 5.7 | 2.98 | 5.16 | 0.58 | 2.91 | 4.68 | 0.62 |
| M5 | 5.4 | 2.73 | 8.00 | 0.36 | –4.19 | 6.24 | **–0.67** |
| M6 | 10.7 | 8.00 | 22.51 | 0.36 | –8.97 | 15.75 | **–0.57** |
| M7 | 4.0 | 1.35 | 1.31 | 1.03 | 1.91 | 1.20 | 1.60 |
| M8 | 7.2 | 4.53 | 3.77 | 1.20 | 6.16 | 3.44 | 1.79 |
| M9 | 14.5 | 11.80 | 15.32 | 0.77 | 10.43 | 15.27 | 0.68 |
| M10 | 6.5 | 3.78 | 6.96 | 0.54 | 3.08 | 6.94 | 0.44 |
| M11 | 0.8 | –1.87 | 0.94 | –1.99 | –1.86 | 0.92 | –2.03 |
| M12 | 1.4 | –1.26 | 12.15 | –0.10 | 0.57 | 11.26 | 0.05 |
| M13 | 2.3 | –0.37 | 13.83 | –0.03 | 0.22 | 10.20 | 0.02 |
| M14 | 8.1 | 5.42 | 29.34 | 0.18 | 13.08 | 27.09 | 0.48 |
| M15 | 5.9 | 3.18 | 11.92 | 0.27 | –0.26 | 9.63 | **–0.03** |
| M16 | 7.7 | 5.04 | 6.39 | 0.79 | 2.67 | 5.90 | 0.45 |
| M17 | 7.1 | 4.43 | 13.73 | 0.32 | –7.39 | 11.09 | **–0.67** |
| M18 | 2.2 | –0.49 | 4.03 | –0.12 | –2.21 | 3.76 | –0.59 |
| M19 | 5.0 | 2.27 | 8.04 | 0.28 | 2.84 | 7.84 | 0.36 |
| M20 | 6.2 | 3.52 | 39.21 | 0.09 | 3.27 | 23.87 | 0.14 |
| M21 | 5.9 | 3.24 | 23.98 | 0.13 | –5.01 | 15.87 | **–0.32** |
| M22 | 8.0 | 5.31 | 8.88 | 0.60 | –0.54 | 7.68 | **–0.07** |
| M23 | 9.9 | 7.24 | 11.57 | 0.63 | 7.71 | 11.04 | 0.70 |
| M24 | 2.7 | –0.02 | 6.56 | 0.00 | 0.22 | 3.92 | 0.06 |
| M25 | 17.6 | 14.90 | 8.91 | 1.67 | 12.73 | 8.34 | 1.53 |
| M26 | 25.7 | 22.98 | 14.82 | 1.55 | 25.99 | 14.28 | 1.82 |
| M27 | 2.7 | –0.04 | 5.89 | –0.01 | –0.42 | 4.34 | –0.10 |
| M28 | 5.7 | 3.02 | 3.86 | 0.78 | 3.51 | 3.79 | 0.93 |
| M29 | 22.7 | 19.97 | 12.74 | 1.57 | 19.53 | 12.14 | 1.61 |
| M30 | 10.0 | 7.27 | 22.39 | 0.32 | 3.32 | 14.42 | 0.23 |
| M31 | 3.7 | 1.02 | 13.90 | 0.07 | –1.71 | 8.18 | **–0.21** |
| M32 | 10.3 | 7.62 | 13.71 | 0.56 | 8.50 | 9.07 | 0.94 |
| M33 | 14.7 | 11.98 | 19.49 | 0.61 | 12.72 | 18.29 | 0.70 |
| M34 | 5.7 | 2.98 | 3.47 | 0.86 | 1.72 | 2.99 | 0.57 |
| Average | 8.14 | 5.45 | | 0.47 | 3.84 | | 0.34 |
| Max | 25.70 | 22.98 | | 1.67 | 25.99 | | 1.81 |

| | | | | | |
|---|---|---|---|---|---|
| Median | 6.30 | 3.61 | 0.45 | 2.29 | 0.29 |
| Min | 0.80 | –1.87 | –1.99 | –8.97 | –2.02 |

Note: Data are based on 72 monthly observations, the yearly average return is the full return achieved by the fund, the yearly excess return is calculated by subtracting the risk-free rate from the full return achieved by the fund, the yearly alpha is the annualized alpha coefficient estimated from the factor model for each investment manager, the tracking error is the standard deviation of annualized alpha returns, *IR* and *IR** are defined according tot he text.

**Table 2: The performance of the individual foreign exchange investors between 2001-2006 based on Pojarliev and Levich (2008) p. 25. In own edition in bold highlighting those occasions, where the Information Ratio changes from positive value to negative when calculating the beta-rates corrected values of Alpha Ratio**

### 1.3.4. Manipulation-proof Performance Measures

In this subchapter we present a new and not yet widespread measure, the Manipulation-proof Performance Measures and the literature of their practical application. These measures in addition to absolute return funds offer solution to a problem, the question of performance manipulation, which makes the performance evaluation of all investment funds and hedge funds difficult. In the dissertation we do not use the term “manipulation-proof” in the sense of non-manipulability from the Gibbard–Satterthwaite theorem well known in microeconomics (See, for example, Mas-Colell et al. (1995) Chapter 23). Here, the focus is not on how vulnerable a social choice function is to manipulation. Instead, what is attempted here is to prevent fund managers from boosting their own performance-based remuneration and bonuses simply by being familiar with the performance measure which is used to assess them. Fund managers who have no material extra knowledge or information to base their investment decisions on, but are aware of the weaknesses of the measure used for assessing them should not be able to make decisions that do not in fact increase the utility of the investors holding the investment fund but still raise the value of the assessment measure. The goal is to use an assessment system that rewards only those investment decisions that truly enhance the utility of investors, those that can only be made by fund managers who have more information or better skills than the market, and use these to effectively and profitably deviate from the market benchmark portfolio’s composition.

It has already been demonstrated (Ingersoll et al. (2007)) that there are trading and reporting techniques that boost the value of traditional performance measures without actually increasing the investors' utility on the risk-return spectrum. These methods can be best illustrated the easiest in the case of the Sharpe ratio, because it has a relatively simple structure: it compares the excess return over the risk-free rate to the standard deviation of the portfolio.

- One *possible manipulation is so-called return smoothing*, when fund managers report their losses stretched out and averaged out for a longer period, for example by subjectively stating assets that are illiquid, rarely priced and difficult to assess (Abdulali 2006). The reported average excess return does not change, but the detected standard deviation declines, and therefore ultimately the risk-adjusted performance appears to improve.
- There is also so-called *dynamic manipulation* when, for example, after a lucky gain at the beginning of the period under review the fund manager protects the profits by resorting to risk-free investments for the remaining period, making the risk-adjusted performance high, since its standard deviation will be close to zero. However, this choice is still suboptimal, and it does not provide the greatest utility to investors, because the fund manager should probably hold some risky assets in the remaining period, too. Ingersoll et al. (2007) present other investment strategies using options as well, which result in unreasonably high Sharpe ratio values: For example, the fund manager sells an OTM option with 1-month maturity at the beginning of the period, and the money from that as well as the already existing funds are invested in risk-free assets. If the option expires worthless (the probability of this is strictly positive), the fund manager achieves positive returns with zero standard deviation and thus an infinite Sharpe ratio. Due to the positive probability, the expected value of this strategy also generates an infinite Sharpe ratio.

*Based on interviews with Hungarian investment fund managers* the first type manipulation, the *possibility of return smoothing in case of Hungarian investment funds seem less probable* as the net asset values of investment funds are defined by custodians independent from the investment managers on a daily frequency and thus this kind of manipulation seem realistic rather only for real estate funds

At the same time, the second type of anomaly, which literature has given the name of *dynamic manipulation, may occur relatively often* in the Hungarian market. It is worth mentioning, at the same time, that in most cases these are *not conscious* investment management decisions, they may not be intended to knowingly gaming the performance measures, but rather a kind of management risk aversion strategy, which leads to sub-optimal decisions if for example the fund manager already exceeded the benchmark rate with an expected extent, on which his bonus is dependent too, and because of this in the rest of the year he defends' the performance by fleeing into risk-free investment for the rest of the year and so misses more profit promising investment opportunities too.

We will no longer distinguish between the two types of return manipulation detections in the followings since none of the statistical methods at our disposal can provide an accurate explanation on the background of the anomalies detected. At the same time, considering the above, we can assume that we will primarily find traces of sub-optimal dynamic manipulation.

Ingersoll et al. (2007) have also shown that there may exist properly constructed performance measures that are able to eliminate the above-mentioned problems based on a utility approach. The results of manipulation-proof performance measures cannot be improved by smoothing in the reports, in other words returns reported averaged out, leaving the average return unchanged. Moreover, the value of manipulation-proof performance measures can only be increased by deviating from the market benchmark portfolio by overweighting certain investment elements. These investment decisions are based on fund managers' extra information compared to the market or their ability to create genuine value added, thanks to their timing and selection skills.

Another advantage is that these measures' assumptions do not include the normal distribution of returns, and therefore their results are less distorted in the case of a skewed or fat-tailed distribution of returns, in contrast to traditional performance measures that typically assume normal distribution and thus are more sensitive to the distortions caused by the abnormal distributions seen in real life. (Ingersoll et al. (2007)).

In case of classic measures Ingersoll et al. (2007) have shown, that they can be manipulated, moreover they have also shown how exactly they can be manipulated.

Manipulation-proof performance measures (MPPMs) are characterised by the following conditions:

1. They should generate a single valued score for ranking.
2. The score should not depend upon the portfolio's monetary value, only the return percentage[3].
3. Uninformed investors should not achieve a higher estimated score by deviating from the benchmark, however, informed investors should be able to do so by taking advantage of arbitrage opportunities
4. The measures should be consistent with standard financial market equilibrium conditions.

If any of these conditions is not met, there is at least one way for active portfolio managers to enhance or manipulate their score by using strategies that result in seemingly better risk-return distributions but in reality achieve the higher score without genuine performance and without increasing the utility of investors.

The first condition excludes the measures that only make an incomplete ranking as well as the useless ones that, for example, merely list the returns.

The second condition simply states that returns in themselves are sufficient statistics, while monetary gains and losses are not. For instance, the absolute net asset value of the fund cannot be relevant in ranking. Just because one fund has more assets than the other, the former does not necessarily perform better.

The third and fourth conditions express that uninformed investors cannot profit by deviating from the benchmark, for example by trying to change the investment fund's

[3] From the perspective of investor utility and so of methodology too truly only the performance of the investment fund matters. However, it should be noted that the size of the fund affects the distribution of management costs and fees among investors, and thus their specific measure, and investment opportunities for too small and too large investment funds too, so in practice it may influence investors' return reduced with costs.

score on the observable data, whereas the exploitation of arbitrage opportunities should be reflected in the score. The measure should not be enhanced without value or information added by, for example, using simple return smoothing, the manipulated reporting of averaged returns or completely shifting to risk-free investments after a lucky streak to reduce volatility.

At the same time, the measure should detect the investment decisions that genuinely increase utility, and consequently assign higher and higher scores to these results. The authors show that these conditions are fulfilled if the measure is:

1. Increasing for the returns (monotonic),
2. Concave,
3. Time separable,
4. Has a power function form.

The first condition ensures that the measure acknowledges arbitrage opportunities. The second prevents the achievement of higher scores merely by increasing leverage or adding unpriced risk. In other words, not only the returns but also the risks taken matter. The third condition prevents dynamic or temporal manipulation. The fourth ensures consistency with the financial market equilibrium theory, and the different returns should be taken from different times to replace returns from different outcomes.

The Ingersoll measure, which meets these conditions, is the following:

$$\hat{\Theta} = \frac{1}{(1-\rho)\Delta t} \ln\left(\frac{1}{T}\sum_{t=1}^{T}\left[\frac{1+r_t}{1+r_{ft}}\right]^{1-\rho}\right) \quad , (14)$$

where $\hat{\Theta}$ estimates the risk-adjusted return premium of the investment fund. For a given $\hat{\Theta}$ the portfolio’s score is the same as the annualised return of a continuously compounded risk-free asset, which is higher than the risk-free rate by the value of $\hat{\Theta}$. $r_t$ is the return of the fund, $r_{ft}$ is the risk-free rate.

$\rho$ is the relative risk aversion ratio, which has usually a value between 0.2 and 10 based on empirical evidence found in the literature. Arrow (1971) argues that it is around 1, the results of Szpiro and Outreville (1988) show that it is between 1 and 5, and the average ratio is 2.89. Layard et al. (2008) also observed values of roughly 1. It is approximately 2 according to the studies by Friend and Blume (1975) and Kydland and Prescott (1982). Gandelman and Hernandez-Murillo (2015) claim that it varies across countries, with a typical value of 1, and even the values of outlier countries are within the 0–3 range.

Both the Ingersoll and the Brown measure used risk aversion factors between 2 and 4. Ingersoll et al. (2007) justified this by stating that even though according to empirical data it would be theoretically possible to make the calculations with a broader range, the relative risk aversion factor of between 2 and 4 corresponds to portfolios whose leverage is between 1.75 and 0.75. And this range covers most funds to be ranked. The selected Hungarian investment funds exhibit similar values based on the portfolio reports: out of 32 funds 23, or 72 percent of the funds under review, belong to this range. Brown et al. (2010) decided to use risk aversion factors between 2 and 4 to facilitate comparability to the results by Ingersoll et al. (2007). To ensure comparability here as well, risk aversion factors between 2 and 4 are used in the calculations below.

The MPPM can also be identified with the benchmark index. For the uninformed investors, the benchmark should be a desirable, ideal investment target with a high score. If the lognormal return of the benchmark is $1+r_b$, then the parameter $\rho$ is the following (see Ingersoll et al. (2007)):

$$\frac{\ln[E(1+r_b)]-\ln(1+r_f)}{Var[\ln(1+r_b)]} \quad .$$

Ingersoll et al. (2007) compares the MPPM they recommend with other performance measures. For three risk aversion factors were the difference calculated on the market portfolio and on various portfolios. The risk-free return was 5%, the market premium 12%, while the standard deviation is 20%, which is consistent with the $\rho = 3$ parameter.

According to MPPM the performance of manipulated portfolios fall short of that of the market portfolio (see Table 3). The Sharpe ratio of the portfolio that was manipulated based on the Sharpe ratio has exceeded the value of the market portfolio in 82.6% of the cases, while at 5% confidence level it was outperforming in 20.4% of the cases compared to the market measured in Sharpe ratio. In contrast, in fact, the portfolio only beat the market portfolio in 46.3% of the cases, measured in MPPM, and was significantly better only in 0.2% of the cases. In addition, 1.4% of cases it significantly underperformed measured in Sharpe ratio, while measured in MPPMs in fact 9.1% of the cases.

| The performance measure based on which the portfolio was manipulated | Value based on own measure | | | Ranking based on the Manipulation-proof Performance Measure (MPPM θ) | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | MPPM θ (ρ = 2) | | | MPPM θ (ρ = 3) | | | MPPM θ (ρ = 4) | | |
| | Win freq. (%) | Freq. signif. + (%) | Freq. signif. - (%) | Mean θ portf- θ mkt (%) | Freq θ portf > θ piac (%) | Freq signif +/- (%) | Mean θ portf- θ mkt (%) | Freq θ portf > θ piac (%) | Freq signif +/- (%) | Mean θ portf- θ mkt (%) | Freq θ portf > θ piac (%) | Freq signif +/- (%) |
| Sharpe *S* | 82.6 | 20.4 | 1.4 | | | | | | | | | |
| Alpha α | 92.4 | 37.6 | 0.2 | -0.84 | 46.3 | 0.2 | -0.96 | 46.3 | 0.4 | -1.08 | 46.0 | 0.5 |
| Gen $\alpha^{gen}$ | 90.6 | 34.0 | 0.3 | | | 9.1 | | | 9.6 | | | 9.9 |
| Sortino *D* | 83.6 | 16.6 | 1.6 | -1.14 | 42.0 | 0.6 | -1.04 | 42.9 | 1.0 | -0.92 | 44.9 | 1.3 |
| | | | | | | 9.9 | | | 9.7 | | | 8.9 |
| SVP *U* | 83.3 | 20.0 | 2.9 | -1.00 | 46.5 | 0.5 | -0.87 | 48.1 | 0.9 | -0.74 | 49.7 | 1.4 |
| | | | | | | 10.3 | | | 9.9 | | | 9.2 |
| HM value $V_{HM}$ | 71.0 | 14.0 | 2.2 | -0.62 | 45.4 | 3.1 | -1.26 | 38.5 | 2.4 | -1.91 | 33.6 | 1.7 |
| TM value $V_{TM}$ | 70.6 | 13.7 | 2.2 | | | 6.9 | | | 9.2 | | | 11.6 |

**Table 3: The Manipulation-proof Performance Measure based on Ingersoll et al. (2007) p. 1532.**

### 1.3.5. Detecting the manipulated performance with the help of MPPMs

This subchapter introduces how with the help of MPPM the detection of performance manipulation is possible and what practical results the application of these methods has lead to. Brown et al. (2010) presented the Ingersoll et al. (2007) MPPM in an alternative form, which is a linear approximation that enabled the definition of the so called Doubt Ratio (DR), which concludes the change of implied risk aversion from measure values calculated with different risk aversion factors. When the Doubt Ratio shows extreme changes in implied risk aversion, then manipulation is in the background with great probability. They have successfully shown this correlation with the application of alternative statistical methods, which used other different approaches the reporting or rate manipulation. The authors deducted the conclusion from all these that the with the help of the Doubt Ratio rate manipulations can be identified reliably.

Brown et al. (2010) used the following simplification, approximation of MPPM (14):

$$\hat{\Theta}(\rho) = \frac{1}{\Delta t}\left\{\bar{x} + \frac{1-\rho}{2}(s_x^*)^2\right\} \quad , \qquad (15)$$

where $\bar{x}$ is the average of the excess return and $(s_x^*)^2 = s_x^2(T-1)/T$ is the variance of the excess return calculated from the sample, $\rho$ is the relative risk aversion factor.

Brown et al. (2010) tested their version of MPPM on hedge funds and compared their results to other performance measures to reveal the impact of manipulation on the reported returns of the funds. The smoothing of reported returns may be the most common way to manipulate the performance of the funds, as it can reduce the volatility of returns while leaving the average return unchanged. It can improve the value of the Sharpe ratio, but not the value of MPPM, as that builds on the difference of the average and the variance of the excess return.

The authors have analysed the returns of such 1710 hedge funds, which have survived the 2007 crisis, and so they have analysed 73530 monthly returns between January

2004 and July 2007 from the TASS database (Lipper Tradig Advisor Selection System, which involves monthly data of hedge funds)[4].

The authors used five different statistical methods to detect traces of manipulation in the funds' returns. The result shows traces of manipulation. Theoretically, if the classic performance measures can be manipulated while the MPPM not, then the rank-correlation must be high between the classic measures (as classic measures are similarly distorted due to manipulations), while between them and MPPMs calculated with different risk aversion factors low. As it can be seen in table 4, this assumption is satisfied for the sample because the rank-correlation between classic measures is over 0.9 (see for example in the first 8 rows of the first column the rank-correlations of the Sharpe-ratio), while between them and MPPM is around 0.7 (see for example in table 4 in the first 9 columns in the last row the rank-correlations of the MPPM with the classic measures calculated with a risk aversion factor of 3 – signed as MPPM3).

| Performance Measure | Sharpe | Omega | Sortino | Kappa | Calmar | Sterling | Berke | ER on VaR | M Sharpe | MPPM 1 | MPPM2 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Omega | 0.9857 | | | | | | | | | | |
| Sortino | 0.9796 | 0.9892 | | | | | | | | | |
| Kappa | 0.9701 | 0.9761 | 0.9969 | | | | | | | | |
| Calmar | 0.9400 | 0.9398 | 0.9736 | 0.9869 | | | | | | | |
| Sterling | 0.9030 | 0.9070 | 0.9164 | 0.9118 | 0.8846 | | | | | | |
| Berke | 0.9681 | 0.9745 | 0.9928 | 0.9938 | 0.9761 | 0.9228 | | | | | |
| ERonVaR | 0.9697 | 0.9532 | 0.9441 | 0.9333 | 0.9016 | 0.9282 | 0.9440 | | | | |
| M.Sharpe | 0.8675 | 0.8623 | 0.8655 | 0.8591 | 0.8314 | 0.9379 | 0.8683 | 0.8948 | | | |
| MPPM1 | 0.6895 | 0.6837 | 0.6991 | 0.7027 | 0.6999 | 0.6151 | 0.6481 | 0.6181 | 0.5788 | | |
| MPPM2 | 0.7259 | 0.7177 | 0.7317 | 0.7344 | 0.7291 | 0.6478 | 0.6825 | 0.6571 | 0.6139 | 0.9872 | |
| MPPM3 | 0.7545 | 0.7444 | 0.7570 | 0.7588 | 0.7513 | 0.6733 | 0.7092 | 0.6876 | 0.6409 | 0.9747 | 0.9960 |

**Table 4: Rank-correlations between classic and manipulation-proof performance measures (tested on original returns) based on Brown et al. (2010) p. 49.**

[4] The observed return distribution of the hedge funds are tick tailed and skew.

As a control sample the authors have calculated distortion-free replicated returns for the analysed funds with the use of the linear factor model of Hasanhodzic and Lo (2007) (see table 5).

| Performance Measure | Sharpe | Omega | Sortino | Kappa | Calmar | Sterling | Berke | ER on VaR | M.Sharpe | MPPM 1 | MPPM 2 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Omega | 0.9998 | | | | | | | | | | |
| Sortino | 0.9997 | 0.9995 | | | | | | | | | |
| Kappa | 0.9992 | 0.9988 | 0.9998 | | | | | | | | |
| Calmar | 0.9969 | 0.9963 | 0.9979 | 0.9987 | | | | | | | |
| Sterling | 0.9989 | 0.9983 | 0.9994 | 0.9996 | 0.9977 | | | | | | |
| Berke | 0.9987 | 0.9981 | 0.9994 | 0.9997 | 0.9985 | 0.9999 | | | | | |
| ER on VaR | 0.9997 | 0.9993 | 0.9994 | 0.9990 | 0.9970 | 0.9991 | 0.9990 | | | | |
| M.Sharpe | 0.9990 | 0.9988 | 0.9996 | 0.9997 | 0.9982 | 0.9996 | 0.9997 | 0.9992 | | | |
| MPPM1 | 0.9652 | 0.9662 | 0.9651 | 0.9640 | 0.9606 | 0.9610 | 0.9606 | 0.9612 | 0.9616 | | |
| MPPM2 | 0.9541 | 0.9548 | 0.9542 | 0.9535 | 0.9508 | 0.9504 | 0.9503 | 0.9505 | 0.9512 | 0.9883 | |
| MPPM3 | 0.9277 | 0.9279 | 0.9282 | 0.9279 | 0.9260 | 0.9251 | 0.9254 | 0.9251 | 0.9259 | 0.9655 | 0.9868 |

**Table 5 : Rank-correlations between classic and manipulation-proof performance measures (tested on replicated returns) based on Brown et al. (2010) p. 50.**

As expected, the rank-correlation is high between the applied MPPM and the classical performance measures in this case as by definition there is no manipulation in the returns according to their construction.

Table 6 compares the rank-correlation between the Sharpe rate and the MPPM for funds in different fund categories, which were found manipulation-free by five alternative statistical methods (see Undetected rows) or manipulated (see Detected rows). The five alternative method: Hasanhodzic and Lo (2007) hedge fund return replication technique, Bollen and Pool (2009) discontinuity-analysis on returns around 0 using the normal distribution, Abdulali (2006) Bias Ratio, which measures the asymmetry of reported returns, Bollen and Pool (2008) conditional autocorrelation, and Treynor and Mazuy (1966) timing measure. The rank-correlations are, as expected, lower for manipulated funds in general.

| | Fund Style | Convertible Arbitrage | Emerging Markets | Equity Markets Neutral | Event Driven | Fixed Income Arbitrage | Fund of funds | Global Macro | Long/ Short Equity | Managed Futures | Multi-strategy |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Total | MPPMl | 0,905 | 0.244 | 0.854 | 0.456 | 0.702 | 0.655 | 0.906 | 0.735 | 0.932 | 0.659 |
| | MPPM2 | 0,913 | 0.283 | 0.865 | 0.476 | 0.721 | 0.682 | 0.929 | 0.775 | 0.861 | 0.706 |
| | MPPM3 | 0,916 | 0.347 | 0.869 | 0.496 | 0.728 | 0.703 | 0.943 | 0.806 | 0.820 | 0.731 |
| | N | 38 | 98 | 65 | 135 | 55 | 531 | 53 | 489 | 125 | 121 |
| Not detectedt (N=l,316) | MPPMl | 0,962 | 0.359 | 0.913 | 0.498 | 0.746 | 0.700 | 0.936 | 0.761 | 0.945 | 0.721 |
| | MPPM2 | 0,970 | 0.386 | 0.925 | 0.522 | 0.762 | 0.731 | 0.953 | 0.802 | 0.864 | 0.765 |
| | MPPM3 | 0,973 | 0.439 | 0.929 | 0.541 | 0.768 | 0.752 | 0.958 | 0.833 | 0.816 | 0.791 |
| | N | 22 | 77 | 57 | 92 | 45 | 403 | 42 | 392 | 104 | 82 |
| Detected (N=394) | MPPMl | 0,721 | -0.243 | 0.714 | 0.497 | -0.103 | 0.654 | 0.764 | 0.593 | 0.832 | 0.631 |
| | MPPM2 | 0,753 | -0.129 | 0.714 | 0.511 | -0.103 | 0.666 | 0.800 | 0.623 | 0.797 | 0.638 |
| | MPPM3 | 0,753 | -0.094 | 0.714 | 0.530 | -0.103 | 0.676 | 0.827 | 0.654 | 0.842 | 0.641 |
| | N | 16 | 21 | 8 | 43 | 10 | 128 | 11 | 97 | 21 | 39 |

**Table 6: Rank-correlation between the Sharpe-ratio and MPPM grouped by investment style based on Brown et al. (2010) p. 56.**

The Brown et al. (2010) version of the MPPM enabled the simple calculation of the implied risk aversion factor, which the authors called Doubt Ratio (DR):

$$\text{Doubt Ratio} = \text{DR} = \frac{\hat{\Theta}(2)}{\hat{\Theta}(2)-\hat{\Theta}(3)} + 2 \approx \frac{2\bar{x}}{(s_x^*)^2} + 1 \ . \qquad (16)$$

If the value of the doubt ratio is extremely high, it suggests extreme risk aversion, which is a potential sign of performance manipulation. Based on Brown et al. (2010) p. 58. table 11, 80% of the funds with Doubt Ratios over 150 were found manipulated by alternative methods too.

The values of the lower and upper quartiles of the Doubt Ratio are slightly higher for the total sample than for the funds classified as non-manipulated by the five alternative methods. In case of funds perceived as manipulated, the values of the Doubt Ratio is scattered over a much larger interval than in the case of funds classified as non-manipulated. At the same time, the global macro, long/short-hedged equity and managed futures groups (Brown et al. (2010) divided the hedge funds into 10 categories based on investment style and strategy) have very low Doubt Ratios for both the manipulated and non-manipulated funds (see table Table *7*).

| Style | | N | Average | Median | Q1 | Q3 | Min. | Max. |
|---|---|---|---|---|---|---|---|---|
| Total | Convertible Arbitrage | 38 | 45.7 | 32.1 | 2.4 | 70.2 | -14.7 | 190.6 |
| | Emerging Markets | 98 | 45.7 | 28.5 | 14.9 | 52.6 | 6.6 | 334.9 |
| | Equity Market Neutral | 65 | 431.4 | 43.1 | 21.4 | 69.1 | -82.3 | 12892.6 |
| | Event Driven | 135 | 87.8 | 66.1 | 37.4 | 134.0 | 8.8 | 257.6 |
| | Fixed Income Arbitrage | 55 | 77.3 | 59.4 | 18.6 | 99.8 | -38.9 | 404.2 |
| | Fund of funds | 531 | 70.9 | 55.5 | 32.8 | 93.2 | -11.8 | 708.8 |
| | Global Macro | 53 | 21.0 | 17.6 | 3.8 | 31.6 | -13.1 | 79.6 |
| | Long/Short Hedged Equity | 489 | 24.3 | 25.1 | 13.5 | 39.9 | -3850.9 | 719.6 |
| | Managed Futures | 125 | 5.1 | 2.4 | -0.9 | 7.0 | -59.8 | 129.7 |
| | Multistrategy | 121 | 57.4 | 32.3 | 14.5 | 90.9 | -23.2 | 385.2 |
| | Total | 1710 | 63.5 | 35.1 | 14.9 | 66.1 | -3850.9 | 12892.6 |
| Not Detected | Convertible Arbitrage | 22 | 22.1 | 11.3 | -4.8 | 33.3 | -14.7 | 130.1 |
| | Emerging Markets | 77 | 39.2 | 23.9 | 14.7 | 40.2 | 6.6 | 334.9 |
| | Equity Market Neutral | 57 | 37.4 | 40.1 | 19.3 | 51.4 | -82.3 | 115.7 |
| | Event Driven | 92 | 70.6 | 50.0 | 34.1 | 103.0 | 12.3 | 218.2 |
| | Fixed Income Arbitrage | 45 | 58.4 | 36.8 | 12.1 | 74.6 | -38.9 | 314.9 |
| | Fund of funds | 403 | 55.2 | 47.7 | 29.7 | 74.8 | -11.8 | 179.0 |
| | Global Macro | 42 | 20.2 | 17.2 | 3.7 | 30.5 | -7.5 | 79.5 |
| | Long/Short Hedged Equity | 392 | 19.5 | 23.1 | 11.7 | 37.4 | -3850.9 | 719.6 |
| | Managed Futures | 104 | 3.2 | 2.4 | -0.8 | 6.5 | -59.8 | 66.5 |
| | Multistrategy | 82 | 40.1 | 23.5 | 13.4 | 50.0 | -5.1 | 227.7 |
| | Total | 1316 | 37.3 | 30.5 | 13.0 | 55.2 | -3850.9 | 719.6 |
| Detected | Convertible Arbitrage | 16 | 78.2 | 70.0 | 46.6 | 115.4 | -10.6 | 190.6 |
| | Emerging Markets | 21 | 69.5 | 36.6 | 25.7 | 86.7 | 14.4 | 254.0 |
| | Equity Market Neutral | 8 | 3238.5 | 133.8 | 98.9 | 6263.4 | 23.3 | 12892.6 |
| | Event Driven | 43 | 124.6 | 134.0 | 65.2 | 170.7 | 8.8 | 257.6 |
| | Fixed Income Arbitrage | 10 | 162.2 | 105.8 | 64.3 | 229.4 | 47.3 | 404.2 |
| | Fund of funds | 128 | 120.6 | 93.4 | 50.4 | 151.9 | -6.9 | 708.8 |
| | Global Macro | 11 | 23.7 | 23.0 | 6.7 | 38.8 | -13.1 | 63.6 |
| | Long/Short Hedged Equity | 97 | 43.5 | 35.0 | 19.1 | 55.5 | -6.3 | 286.8 |
| | Managed Futures | 21 | 14.4 | 2.6 | -4.2 | 17.3 | -15.4 | 129.7 |
| | Multistrategy | 39 | 93.8 | 97.2 | 29.7 | 121.1 | -23.2 | 385.2 |
| | Total | 394 | 151.0 | 62.7 | 26.8 | 129.4 | -23.2 | 12892.6 |

The Doubt Ratio can be calculated from the MPPM calculated with two different risk aversion factors. $DR = \Theta(2) / (\Theta(2) - \Theta(3)) + 2$. The Q1 and Q3 quartiles spread across 14.9 and 66.1 for all funds, while for non-detected funds they are somewhat lower between 13.0 and 55.2, and detected funds have a much wider interval, than non-detected funds, the value of Q3 quartile is almost 3-times higher than of non-detected funds with 129.4.

**Table 7: Comparison of the Doubt Ratios grouped by the manipulation signals of the different alternative methods based on Brown et al. (2010) p. 57.**

There are 34 hedge funds with Doubt Ratios of over 150 at a 5 percent significance level, representing 2 percent of the total sample under review. 80 percent of these 34 funds According to the results 34 funds have Doubt Ratios above 150 on a 5% confidence level, which is 2% of the sample tested[5]. 80% of these 34 funds were assessed suspicious by the alternative five statistical methods, and an extremely high Doubt Ratio is a good indicator of possible performance manipulation or return manipulation (see table Table 8).

| Style | Not detected | | | Detected | | | Total |
|---|---|---|---|---|---|---|---|
| | < 1% | < 5% | % | < 1% | < 5% | % | |
| Convertible Arbitrage | 0 | 0 | 0.0% | 0 | 0 | 0.0% | 38 |
| Emerging Markets | 1 | 1 | 1.0% | 2 | 2 | 2.0% | 98 |
| Equity Market Neutral Neutral | 0 | 0 | 0.0% | 3 | 3 | 4.6% | 65 |
| Event Driven | 0 | 2 | 1.5% | 2 | 5 | 3.7% | 135 |
| Fix Income Arbitrage Arbitrage | 1 | 1 | 1.8% | 0 | 2 | 3.6% | 55 |
| Fund of funds | 0 | 0 | 0.0% | 9 | 11 | 2.1% | 531 |
| Global Macro | 0 | 0 | 0.0% | 0 | 0 | 0.0% | 53 |
| Long/Short Hedged Equity | 1 | 1 | 0.2% | 0 | 1 | 0.2% | 489 |
| Managed Futures | 0 | 0 | 0.0% | 0 | 0 | 0.0% | 125 |
| Multistrategy | 1 | 2 | 1.7% | 1 | 3 | 2.5% | 121 |
| Total | 4 | 7 | 0.4% | 17 | 27 | 1.6% | 1710 |

This table shows how many investment funds are located per investment style with a Doubt Ratio significantly higher than 150. At a level of 5% significance, there are a 34 funds of the total sample with Doubt Ratios greater than 150, which is about 2% of the funds examined. 80% of the 34 detected funds were qualified suspicious by alternative methods too, thus, the analysis of the Doubt Ratio is consistent with other methods, and an extremely high Doubt Ratio can be the indicator of suspicious funds. The convertible arbitrage, global macro, the long/short hedged equity, and the managed futures groups consist of very few suspicious funds according to the Doubt Ratio, which indicates that these investment styles are less likely to be subject to manipulations. Other investment styles are relatively more exposed to manipulation: in case of the emerging markets, equity market neutral, event driven, fix income arbitrage, fund of funds and multistrategy funds 2.5-4% is the ratio of suspicious funds within their categories. The ratio of suspicious funds is especially high, above 4% in case of the equity market neutral, event driven, fix income arbitrage and multistrategy. In case of two equity market neutral funds we find Doubt Ratios over 12 000.

**Table 8: Funds with extremely high Doubt Ratios based on Brown et al. (2010) p. 58.**

[5] Note, that there frequently exist Doubt Ratios over 150 among hedge fund types with lower volatility too.

### 1.3.6. Alternative ways of detecting manipulated performance, return smoothing: Bias Ratio, Discontinuity-analysis

While the Doubt Ratio measures changes in the implied risk aversion coefficient based on MPPM values, other techniques also exist, which conclude potential smoothing or other manipulation of returns from to the characteristics of the return distribution and/or the distribution of yields around 0. This subchapter describes alternative ways of detecting return manipulation and their application, the Bias Ratio, and discontinuity analysis based on the literature.

Abdulali (2006) introduced the use of Bias Ratio to analyse hedge fund yields. The purpose of the author was specifically to create an easy-to-calculate metric that can filter out hedge funds that presumably use yield smoothing or other manipulation primarily through net asset value of portfolio elements which are infrequently pricing or difficult to measure. The hedge funds filtered this way should then be subjected to more detailed analysis, including a separate analysis of the value and liquidity of the portfolio of the hedge funds. Advantage of the Bias Ratio is that it can be used to pre-filter the funds where it is worthwhile and necessary to implement analyses of the composition and value of their portfolio whereas in the past, in the absence of such an instrument, these more detailed calculations had to be carried out in order to evaluate all hedge funds that represent investment targets to uncover possible yield manipulation.

The Bias Ratio is a formula that is easily calculated from the return distribution of hedge funds or investment funds, which is a concrete measure of the bias that can be found in the valuation of fund assets: It measures the shape of the return distribution in a critical band around the 0 return, indicating hedge funds or investment funds that are subject to return smoothing.

$$\text{Bias Ratio} = \frac{\text{Observed frequency } (r_i) : r_i \in [\ 0,\ \ +1.0\sigma\ ]}{1 + \text{Observed frequency } (r_i) : r_i \in [\ -1.0\sigma,\ \ 0\ )}\ , \qquad (17)$$

where [0.0, +1.0σ] is a closed interval, including 0, inclusive of returns up to + 1 standard deviation. The [-1.0σ, 0.0) is a half-closed interval from the return -1 standard deviation to 0, including the -1 standard deviation, but not 0. Observed returns are indicated by $r_i$.

The Bias Ratio approximates the area under the first and second quartile curves and has the following properties:

1. $0 \leq TR \leq n$, where n the number of observed returns.
2. $\forall\ r_i$-re, if $r_i$<0, then TR=0
3. $\forall\ r_i$-re, if $r_i$ >0, $r_i > +1.0\sigma$, then TR=0
4. If $r_i$ follows a normal distribution, 0 with expected value, then TR $\rightarrow$ 1, if n $\rightarrow$ $\infty$.

Hedge funds and investment funds with 0 average and normal distributions have a Bias Ratio of less than 1, and theoretically there is little demand for them. Observations support this, as large market indices have a Bias Ratio greater than 1. Funds and investment strategies investing in cash and T-bill-like instruments generate relatively constant positive returns, with very rare loss periods, which result in a right skewed distribution around 0 and consequently, also with a high Bias Ratio. Thus, according to Abdulali (2006), the use of the Bias Ratio is less reliable for investment funds or hedge funds that have high cash-type investments.

According to the observation of Abdulali (2006), major stock indices have a Bias Ratio between 1 and 1.5. The Bias Ratios of stock-based hedge funds studied by Abudali (2006) were within the range of 0.3 to 3 with an expected value of 1.29 and a standard deviation of 0.5. For hedge fund groups that follow a different investment style, the Bias Ratio values, as well as the averages and medians of each group show a wide variation. According to Abdulali (2006), in the case of investment funds or hedge funds of a given investment style, funds above the calculated median of their Bias Ratios of the group, further analysis of the portfolio composition and pricing process is recommended.

Theoretically, if return smoothing or the creative valuation of illiquid assets are in the background, then we can detect an imbalance in the frequency of positive and negative returns directly at zero toward positive returns. In discontinuity analysis, we look for signs of discontinuity in the distribution of investment funds around 0, which can testify of potential return smoothing. To perform this analysis, the distribution of returns must be plotted on a histogram. Choosing class width is a critical issue for the analysis, following Bollen and Pool (2009) the formula below is advisable to be used based on Silverman (1986):

$$h = 0{,}9 \min \left[\sigma ; \frac{Q3 - Q1}{1{,}34}\right] N^{-0{,}2} \quad , \quad (18)$$

where h is the class width, $\sigma$ is the standard deviation of returns, N is the number of observed returns, Q3 and Q1 are the appropriate quartiles. According to Bollen and Pool (2009) both for the determination of h, and for depicting the histograms exactly 0 returns should be ignored, because they are not representing return smoothing, but missing date or the lack of trading.

Measuring the disproportion between the frequencies of positive and negative returns around 0, according to Bollen and Pool (2009) and Burgstahler and Dichev (1997) is possible by examining how the frequency of positive and negative returns near 0 relate to their own expected value, and whether there is a fracture in the course of distribution relative to neighbouring classes. Since the fracture observed in the distribution is not always clear, we also need numerical statistics to evaluate it. Thus, during the analysis it can be examined how the frequency of yields around 0 statistically compares to the normal distribution with the same expected value and standard deviation as the observations. The statistical test whose values can be used to evaluate the course of distributions that can also be seen on the histograms according to Bollen and Pool (2009) and Burgstahler and Dichev (1997) is as follows:

$$Z = \frac{f - Np}{\sqrt{Np(1 - p)}} \quad , \quad (19)$$

where f is the frequency observed in a given class interval, N is the number of observations, p is the expected value of a class interval based on the normal distribution, which we have calculated from the distribution function of the normal distribution with appropriate moments during our analysis.

Bollen and Pool (2009), Brown et al. (2010) and Burgstahler and Dichev (1997) both found that negative returns around 0 showed a significant negative deviation compared to their expected value, while positive returns proved to be statistically higher than their expected value, supporting the hypothesis that the frequency of positive returns around 0 was probably increased as a result of manipulation against negative returns around 0.

# 2. OWN CALCULATION RESULTS

In chapter 2.1. we present the examined events around the quarterly reports of S&P500 index equities, and the factors that determine sample selection, then perform the analytical steps described in chapter 1.2.

We are looking for answers to the following questions:

1) Whether there are abnormal returns before or after publication, which in the former case indicates leaks and trading on insider information, while in the latter case they indicate a forming trend due to news but both cases mean that the market is not fully efficient.
2) How does the direction and magnitude of EPS-surprises included in company reports affect price reactions during the reporting period?
3) In case of exchange listed companies operating in the technology sector, which have a more uncertain valuation, do abnormal price reactions resulting from greater uncertainty outweigh the reactions of companies in the general equity market?

According to our results, the direction and magnitude of surprise in corporate profitability determine how stock prices change as a result of the announcement. However, there is a shift in the level and direction of the cumulative abnormal yields observed for each news groups to negative price reactions, as a significant positive yield is only seen in the very good news group. The effect of the new information can no longer be observed on the trading days following the announcement and no trend develops in the direction of surprise adequately. Thus, the analysis confirms that the stock market in the selected sample is moderately efficient. Generally, there are significantly higher price reactions in the S&P500 IT index news groups compared to the S&P 500 index.

Chapter 2.2. presents, through our own calculations the valuation of Hungarian absolute return investment funds and the detection of traces of return manipulation or suboptimal investment decisions as a new result, as there is no known example of tracing of return manipulation in the literature in case of Hungarian investment funds.

The following new results were obtained from our analysis:

1) We have compared the results of the Sharpe ratio with the results of MPPM and revealed some traces of return manipulation based on rank correlation
2) As a new result, we have presented differences in value and ranking between different MPPM versions for both MPPM and Doubt Ratio.
3) As an innovation, we recommended the use of Ingersoll et al. (2007) MPPM because of its accuracy against Brown et al. MPPM (2010), both for performance evaluation and for calculating the Doubt Ratio.
4) We analysed the signalling ability of the Doubt Ratio, that is based on the MPPM in exploring return manipulation as well as its relationship to alternative methods, the Bias Ratio, and the discontinuity-analysis.
   i. In contrast to the close overlap of the Doubt Ratio observed in the literature with alternative manipulation detecting methods (80% concurrence based on Brown et al. (2010)), in our sample we found mixed results because alternative methods showed significant anomalies in 4 out of 10 cases, i.e. return manipulation or suboptimal investment decisions with high probability, while the Doubt Ratio identified only 4 investment funds as suspicious of which 1 was also confirmed by alternative methods.
   ii. Overall, therefore, our results suggest that the Bias Ratio was a better pre-filtering tool for more detailed analysis of return manipulation (e.g. discontinuity-analysis) than the Doubt Ratio.
   iii. In case of only one mutual fund, the Concorde Citadella fund seemed suspicious signals to be well grounded based on investment policies and interviews with mutual fund managers, and this fund was marked by both Doubt Ratio and Distortion Ratio.

## 2.1. ANALYSIS OF SURPRISE EFFECTS OF QUARTERLY REPORTS IN CASE OF S&P 500 EQUTIES

In this chapter we examine the impact on stock prices of quarterly reports published by companies in the S&P500 index. The topics discussed in this chapter are based on those described in our working paper, Rácz and Huszár (2018) and in our published article, Rácz and Huszár (2019, p. 251-262). However, it has an extended time series compared to what is described there (Instead of Q1 2015 to Q2 2017, from the first quarter of 2015 until the fourth quarter of 2018 period, i.e. 16 quarters instead of 10 quarters) and extended number of analysed equities (instead of 30-30 stocks per index 45-45 units per index and (instead of 30-30 stocks per index, 45-45 units per index), so, the number of analysed independent quarterly report events increased from 300-300 to 720-720 per index, as well as, instead of the breakdown used for the news category (good-neutral-bad) we applied 5 news categories breakdown (very good, good, neutral, bad, very bad), so that the effect of the EPS-surprise on the price response can be studied not only by the direction of the surprise, but also by its magnitude. Another important difference is that while previously, eight stocks were included in both indices, now each analysed stock can only be listed in case of one or other index, in this way, eliminating methodological issues caused by overlapping.

We deal with closely related issues:

1) Whether there are abnormal returns before or after publication, which in the former case indicates leaks and trading on insider information, while in the latter case they indicate a forming trend due to news but both cases mean that the market is not fully efficient.
2) How does the direction and magnitude of EPS-surprises included in company reports affect price reactions around the reporting period?
3) Is there a difference in price response between different sectors?

We hypothesize that (1) the direction and magnitude of surprise determine the magnitude and direction of price reactions, but its effect is not immediately fully realized in the price, and (2) in the technology sector the impact of surprise is stronger because of the much more uncertain valuation of companies in the industry.

We downloaded most of the data used for analysis from the Bloomberg reporting system in June 2019. The exception is EPS data based on the Zacks Investment Research database (Zacks Earnings Surprises, https://www.zacks.com/stocks/).

## The examined hypotheses

Based on the theories presented in the theoretical review, we believe that stock markets are not fully effective, but this is considered as a starting point, complemented by the phenomena described by behavioural economics. Following all these considerations, we formulate the following hypotheses

1. The direction and magnitude of the surprise in company profitability determines how stock prices change as a result of the announcement and the impact of new information can be observed on the trading days following the announcement too, and a trend develops in line with the direction of the surprise.
2. The effect of the surprise is more pronounced in case of uncertain stocks, including the technology sector.

## The examined hypotheses

The sample selected for the presented event analysis includes given elements of the S&P 500 and S&P 500 Information Technology (Hereinafter referred to as S&P500 IT) stock indices. To test the first hypothesis, we observe the price movement of the indices' first 45-45 stocks with the largest market capitalization as a result of their quarterly reports published between Q1 2015 and Q4 2018, for which we had flawlessly both the price data and analysts' EPS forecasts as well as actual reported EPS results. We used EPS forecasts and EPS results to analyse the impact of the surprise because, on the one hand, the value of the shares is determined by the present value of future EPSs, and, on the other, we have complete forecast and factual data for our investigated shares. So, overall, we are examining 720-720 reports over the 16 quarters, so each selected stock was sampled as 16 separate events. Following the recommendations of MacKinlay (1997), we selected a 21-day trading window covering a 4-week interval for the analysis.

The sample was chosen based on several selection criteria. The observations are directed at large companies which are traded on liquid markets. On the one hand, we avoid methodological problems such as the effect of non-synchronized trading. On the other hand, we avoid anomalies that arise more frequently and more intensively in case of companies with smaller capitalization, that mostly have lower liquidity, making the analysis more reliable.

Our second hypothesis assumes that technology equities are more responsive to EPS-surprises due to uncertainty in their valuation. To test this, we compare the price movements of the quarterly reports of S&P500 and S&P500 IT Index companies 45-45 companies with the largest market capitalization for which we have complete data: price, EPS forecast, actual EPS report (see Table 9). That is, we performed the analysis on a total of two samples consisting of 720-720 non-overlapping observations described below. In case of the second sample, the random sector distribution can no longer be claimed, and this should also be taken into consideration when interpreting the results.

| | S&P500 | S&P500 IT |
|---|---|---|
| 1 | 3M Co | Accenture |
| 2 | Abbott Laboratories | Adobe |
| 3 | Abbvie | Akamai Technologies Inc |
| 4 | Altria Group Inc | Amphenol Corp |
| 5 | Amazon | Analog Devices |
| 6 | American Express Co | ANSYS Inc |
| 7 | American Tower Corp | Apple |
| 8 | AT&T | Applied Materials |
| 9 | Bank of America | Autodesk Inc |
| 10 | Boeing | Automatic Data Processing |
| 11 | Chevron | Broadcom |
| 12 | Cisco | Broadridge Financial Solutions Inc |
| 13 | Citigroup | Cadence Design Systems Inc |
| 14 | Coca-Cola | Cisco |
| 15 | Comcast | Cognizant Technology Solutions |
| 16 | Danaher Corp | Fidelity National Information Services |
| 17 | Eli Lilly & Co | Fiserv Inc |
| 18 | Exxon Mobil | FleetCor Technologies Inc |
| 19 | Facebook | Global Payments Inc |
| 20 | General Electric | HP |
| 21 | Gilead Sciences Inc | IBM |
| 22 | Google | Intel |
| 23 | Home Depot | Intuit |
| 24 | Honeywell International Inc | KLA-Tencor Corp |
| 25 | Johnson & Johnson | Lam Research Corp |
| 26 | JPMorgan Chase | Mastercard |
| 27 | Lockheed Martin Corp | Maxim Integrated Products Inc |

| | | |
|---|---|---|
| 28 | McDonald's Corp | Microchip Technology Inc |
| 29 | Medtronic PLC | Micron Technology |
| 30 | Merck | Microsoft |
| 31 | Netflix Inc | Motorola Solutions Inc |
| 32 | NextEra Energy Inc | NetApp Inc |
| 33 | NIKE Inc | NVIDIA |
| 34 | Pfizer | Qualcomm |
| 35 | Philip Morris | Skyworks Solutions Inc |
| 36 | Procter & Gamble | Symantec Corp |
| 37 | Starbucks Corp | Synopsys Inc |
| 38 | Thermo Fisher Scientific Inc | Take-Two Interactive Software Inc |
| 39 | Union Pacific Corp | TE Connectivity |
| 40 | United Technologies Corp | Texas Instruments |
| 41 | UnitedHealth Group | Total System Services Inc |
| 42 | Verizon | VeriSign Inc |
| 43 | Walmart Inc | Visa |
| 44 | Walt Disney | Western Digital Corp |
| 45 | Wells Fargo | Xilinx Inc |

**Table 9: The analysed equities of S&P500 and S&P 500 IT, that have the highest market capitalization and for which we have the necessary data**

## Details of modelling

Before testing hypotheses, we need to quantify the surprise effect on corporate results. We then estimate the parameters of the regression model used to calculate normal returns, and finally calculate and adequately aggregate the abnormal returns.

### 2.1.1. Analysis of EPS data

The surprise effect of reporting earnings can mainly be captured as the difference of the actual value of earnings per share (EPS) for the period perceived and the consensus of analysts' expectations prior the publication of the company. This is based on the assumption that analyst forecasts will be incorporated in stock prices. Thus, the report itself is less informative on its own in assessing price developments, and comparison with market expectations is essential. The estimated EPS value we use is average of analysts' estimates immediately prior to the company publication. We compare this ratio to the actual earnings per share at the reporting date. Therefore, the factual data do not include later revisions of company results, as these were not yet known to the market at the time of the event. In addition, the actual EPS adjusted data, which has been cleaned of various one-off and extraordinary items, is probably much less sensitive to filtered individual extra items than profit from normal business operations

After collecting the sample data and calculating the EPS surprise, we divided the observations into five groups similar to MacKinlay's (1997) procedure; reports containing very good, good, bad, very bad, or neutral news. The news value of the EPS deviation within the ± 1% band from the analyst consensus is considered neutral, the EPS surprises between + 1% and + 4% good and EPS surprises greater than + 4% very good, in case of negative surprises the same logic with only -1% and -4% limits.

Of the 720 items sampled from the S&P 500, 330 got in the very good, 206 in the good, 91 in the neutral, 30 in the bad, and 63 in the very bad news group, while in the S&P 500 IT this distribution is 411-193-26-15. The two histograms in Figure 2 also show these frequencies. Positive surprises are much more common, and their distribution is skewed to the right. This may be because analysts' estimates are often too conservative, thus negative surprises can be avoided. The sample from the S&P500 IT index shows extreme EPS surprise values much more frequently than the sample from the S&P500.

The distribution of the sample items from the S&P500 IT index is as follows: 1 case shows a negative difference of more than 24% and a positive difference of 58 times exceeding 24% compared to the forecast, while in the S&P 500 sample the same two values are 27, and 40. It is also worth noting that the period under review took place in the upswing of a boom cycle, which was likely to cause more positive surprises.

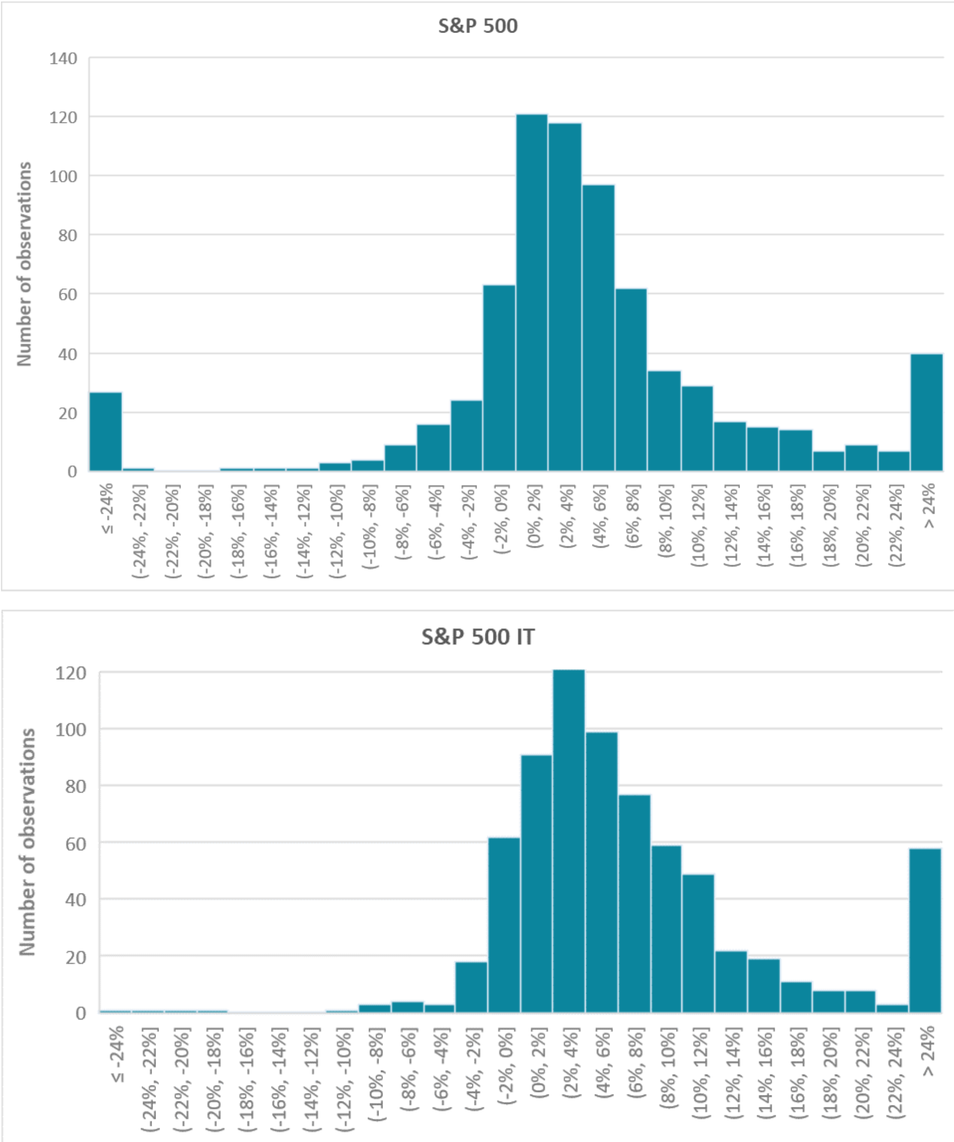


**Figure 2: The distribution of EPS-surprise frequencies in case of observations taken from the S&P 500 and S&P 500 IT indexes.**

### 2.1.2. Parameter estimation and modelling of returns

We compared actual returns with the values of the calculated market model using the regression equation described in (2). In all cases, the estimation period is the *500 trading day interval preceding the observation window for that observation*. This is because model parameters may change as time goes by for individual stocks too. Thus, estimates are made separately for each of the 720-720 observations, not just for each security which increases the explanatory power of the model and makes the calculation of abnormal returns more accurate. The market portfolio in the model is embodied in the S&P 500 stock index for stocks belonging to both of the two analysed stock indices.

From the price data downloaded from Bloomberg's database, we calculated daily logarithmic returns for the individual shares and the S&P 500 and S&P500 IT indices for each relevant observation period. Based on this, we estimated the parameters of the regression model. We fitted linear regressions of 720-720 to the two samples, as the $\hat{\alpha}$ and $\hat{\beta}$ parameters of each stock change over time.

The $R^2$ metrics describing the fit of the models are spread in a very large interval and they have often relatively low values. This is not surprising, of course, since beta expresses only the market risk of the stock, while different idiosyncratic shocks can significantly deviate real returns from the values predicted by the model. Gospodinov and Robotti (2013) also note that although models used to predict returns typically produce low $R^2$ metrics, they are considered to be economically relevant.

### 2.1.3. Calculation and aggregation of abnormal returns

In this subchapter we describe the steps for calculating and aggregating abnormal returns. Now, we come to the most interesting part of the research, the calculation of abnormal returns, which is based on equation (4) In order to test hypotheses, the calculated data points should be aggregated as described in Chapter 1.2.3. On the one hand, it is clear that the five groups within the sample (very good, good, neutral, bad and very bad news) should be examined separately, so we calculate the average abnormal returns of the groups for each period of the event window according to (5). The question is how to aggregate on time between $\tau_1$ and $\tau_2$ periods to test the appropriate hypotheses.

| $\tau$ | S&P 500 | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Very good news | | Good news | | Neutral news | | Bad news | | Very bad news | |
| | AR | CAR | AR | CAR | AR | CAR | AR | CAR | AR | CAR |
| -10 | 0.00% | 0.00% | 0.17% | 0.17% | 0.39% | 0.39% | -0.18% | -0.18% | -0.97% | -0.97% |
| -9 | 0.11% | 0.12% | 0.01% | 0.18% | -0.14% | 0.25% | 0.08% | -0.10% | -0.60% | -1.57% |
| -8 | 0.06% | 0.18% | 0.14% | 0.32% | 0.06% | 0.31% | -0.78% | -0.88% | -0.30% | -1.87% |
| -7 | -0.13% | 0.05% | -0.17% | 0.15% | 0.16% | 0.47% | 0.05% | -0.83% | -0.67% | -2.55% |
| -6 | 0.15% | 0.20% | 0.11% | 0.25% | -0.27% | 0.20% | 0.27% | -0.56% | -0.01% | -2.56% |
| -5 | -0.03% | 0.17% | -0.30% | -0.04% | -0.16% | 0.04% | -0.73% | -1.29% | -0.01% | -2.57% |
| -4 | -0.06% | 0.11% | -0.02% | -0.06% | -0.80% | -0.75% | 0.29% | -0.99% | 0.81% | -1.76% |
| -3 | 0.03% | 0.14% | 0.01% | -0.04% | -0.03% | -0.78% | -0.19% | -1.18% | -1.13% | -2.89% |
| -2 | -0.03% | 0.11% | 0.06% | 0.02% | -0.25% | -1.03% | 0.37% | -0.81% | 0.53% | -2.36% |
| -1 | 0.05% | 0.16% | -0.17% | -0.15% | -0.22% | -1.25% | 0.37% | -0.44% | 0.10% | -2.26% |
| 0 | 0.38% | 0.54% | 0.04% | -0.10% | 0.19% | -1.05% | 0.45% | 0.02% | -1.65% | -3.91% |
| 1 | 1.06% | 1.60% | -0.05% | -0.16% | -0.64% | -1.69% | -3.20% | -3.19% | -4.39% | -8.29% |
| 2 | 0.07% | 1.67% | -0.08% | -0.24% | -0.24% | -1.94% | -0.18% | -3.37% | 0.52% | -7.77% |
| 3 | -0.16% | 1.51% | 0.18% | -0.05% | 0.08% | -1.86% | 0.05% | -3.32% | 0.26% | -7.51% |
| 4 | 0.06% | 1.57% | -0.12% | -0.17% | 0.06% | -1.79% | 0.13% | -3.19% | 0.54% | -6.98% |
| 5 | 0.11% | 1.68% | -0.12% | -0.29% | -0.06% | -1.85% | -0.36% | -3.55% | 0.50% | -6.48% |
| 6 | -0.04% | 1.64% | 0.16% | -0.14% | -0.07% | -1.92% | 0.04% | -3.52% | -0.38% | -6.86% |
| 7 | 0.10% | 1.75% | 0.06% | -0.08% | -0.14% | -2.06% | 0.26% | -3.26% | 0.14% | -6.72% |
| 8 | 0.05% | 1.79% | 0.07% | -0.01% | 0.01% | -2.05% | -0.42% | -3.68% | 0.02% | -6.71% |
| 9 | -0.07% | 1.73% | -0.08% | -0.09% | -0.24% | -2.29% | 0.35% | -3.33% | -0.41% | -7.11% |
| 10 | -0.09% | 1.63% | -0.01% | -0.11% | 0.43% | -1.86% | 0.02% | -3.30% | 0.48% | -6.63% |

| τ | S&P 500 IT | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Very good news | | Good news | | Neutral news | | Bad news | | Very bad news | |
| | AR | CAR | AR | CAR | AR | CAR | AR | CAR | AR | CAR |
| -10 | 0.11% | 0.11% | -0.02% | -0.02% | 0.03% | 0.03% | 0.04% | 0.04% | 0.03% | 0.03% |
| -9 | 0.04% | 0.15% | 0.02% | 0.00% | -0.08% | -0.05% | -0.10% | -0.07% | -0.17% | -0.14% |
| -8 | 0.08% | 0.23% | 0.03% | 0.02% | -0.04% | -0.09% | -0.15% | -0.21% | -0.07% | -0.21% |
| -7 | 0.14% | 0.37% | 0.03% | 0.05% | 0.07% | -0.02% | -0.08% | -0.29% | -0.01% | -0.22% |
| -6 | 0.03% | 0.41% | -0.15% | -0.10% | -0.11% | -0.13% | 0.08% | -0.21% | 0.09% | -0.12% |
| -5 | -0.02% | 0.39% | -0.13% | -0.23% | -0.03% | -0.16% | 0.31% | 0.10% | 0.01% | -0.11% |
| -4 | -0.06% | 0.33% | -0.06% | -0.29% | 0.09% | -0.07% | -0.03% | 0.07% | 0.00% | -0.11% |
| -3 | 0.00% | 0.32% | 0.11% | -0.17% | 0.04% | -0.03% | -0.01% | 0.06% | 0.21% | 0.10% |
| -2 | 0.00% | 0.32% | -0.06% | -0.24% | 0.10% | 0.07% | -0.10% | -0.04% | 0.01% | 0.11% |
| -1 | -0.15% | 0.17% | -0.05% | -0.28% | -0.10% | -0.04% | 0.13% | 0.08% | 0.15% | 0.26% |
| 0 | 0.89% | 1.06% | 0.07% | -0.21% | -0.77% | -0.80% | -1.80% | -1.72% | -0.40% | -0.14% |
| 1 | 0.29% | 1.35% | 0.16% | -0.05% | -0.15% | -0.95% | -1.08% | -2.80% | -1.11% | -1.25% |
| 2 | -0.17% | 1.18% | -0.09% | -0.15% | 0.08% | -0.87% | -0.22% | -3.03% | -0.24% | -1.49% |
| 3 | -0.16% | 1.02% | -0.05% | -0.20% | 0.02% | -0.85% | 0.20% | -2.83% | -0.14% | -1.63% |
| 4 | -0.07% | 0.95% | -0.03% | -0.23% | -0.04% | -0.89% | -0.17% | -3.00% | 0.02% | -1.61% |
| 5 | -0.16% | 0.79% | 0.08% | -0.15% | -0.11% | -1.00% | 0.02% | -2.98% | -0.11% | -1.71% |
| 6 | -0.13% | 0.66% | -0.04% | -0.19% | -0.17% | -1.18% | 0.11% | -2.87% | -0.04% | -1.75% |
| 7 | -0.02% | 0.64% | 0.03% | -0.16% | 0.08% | -1.09% | 0.22% | -2.65% | -0.08% | -1.83% |
| 8 | 0.02% | 0.66% | -0.02% | -0.18% | 0.12% | -0.97% | -0.52% | -3.18% | -0.12% | -1.95% |
| 9 | 0.05% | 0.71% | 0.07% | -0.11% | -0.09% | -1.06% | 0.16% | -3.02% | -0.03% | -1.98% |
| 10 | 0.06% | 0.77% | -0.06% | -0.17% | -0.02% | -1.08% | -0.25% | -3.27% | 0.25% | -1.73% |

**Table 10: The average and cumulative average abnormal returns of the five surprise categories in the period around the event in case of the sample taken from the two indexes.**

There are two ways to test whether the direction of surprise is in line with the movement of prices. One solution is to consider the cumulative abnormal return over the entire event window $\overline{CAR}(-10,10)$. However, assuming that the information is immediately incorporated in the prices, a logical choice is $\overline{CAR}(0,1)$, which includes the date of announcement and the day immediately following it, and $\overline{CAR}(0,10)$ too, where only the average abnormal returns observed on the trading day or days following the event are cumulated. Unfortunately, as we do not have information on exactly when the analysed reports occurred during the day, we need to use the $\overline{CAR}(0,1)$ to measure the impact of reports published after the trading period to investigate the immediate impact of the reports. And whether the momentum after the report is observable in the price is obviously to be examined with a shifted window, such as $\overline{CAR}(2,10)$. While possible leakage of insider information $\overline{CAR}(-10,-1)$ can indicate.

Table 10 and Figure 3 clearly shows the impact of quarterly reports on stock prices. Until the pre-announcement trading day, minimum abnormal returns can be observed in each group of the S&P 500 index. The same trend can be said for the abnormal pre-announcement returns of the very good and good groups of the S&P500 IT. However, in the neutral, bad and very bad news groups based on the data we can see significant negative cumulative abnormal returns already in the days leading up to the announcement. Cumulative abnormal returns of the two extreme groups at the time of publication for both the S&P 500 and S&P 500 IT indices fire out according to the direction of the surprise.

In general, we can see a well-formed positive connection between the size of the surprise and the size of the experienced abnormal returns, however as described above the asymmetry in the direction of negative news is general. While in the very good news group after the announcement the abnormal return stabilizes around 1% and 2% respectively for the two indices, and in case of good news its value is negative but very close to zero, in the bad news group it is stabilizing around -2% and -3%, in case of very bad news -3% and -7%. In the groups of the neutral news after the announcement the cumulated abnormal return stabilises around -1% and -2%. The fact that the market responds to neutral and slightly positive EPS surprises with negative abnormal returns in general, supports the view that during a period that can be described as a boom in economic activity, market participants' expectations are very high and even an otherwise positive or neutral quarterly fact data can be disappointing if it falls short of their expectations.

The bad group of the S&P 500 index is comparable with the abnormal yields of S&P500 IT. However, while the very bad newsgroups of the later shows very high negative cumulative abnormal yields, in case of the first one the cumulative abnormal yield o f-2% is a somewhat surprising result. This means that the market penalizes mor for EPS surprises in the band of -1 and -4% in general in the case of the S&P 500 index, than for EPS-surprises of more than -4%.

It is clear that, even the trading day after the report has a strong surprise effect caused by late stock hours or post-close disclosures. From the second trading day after the announcement, however, there is only a minimal change in the cumulative average abnormal return in each newsgroup and both indices. The new information is integrated into the share price and abnormal returns continue to be around zero.

Observing the magnitude of the shift in cumulative abnormal returns, we can see values scattered in the 0-8.3 percentage point band. Before we are misled by these values not-so-high comparable to stock markets, note that these are just *abnormal* returns, of which most of the other market effects have already been filtered by modelling expected returns. Moreover, we look at average values for a whole group of equities, but in individual cases it is not uncommon in the sample to have an abnormal double-digit daily return.

Similar to $\overline{CAR}(-10{,}10)$, cumulative average abnormal returns can be analysed over any interval $(\tau_1, \tau_2)$. Tables 10 and 11 show these results during the hypothesis test. However, considering that the proportion of EPS surprises in the positive range is significantly higher in both sample groups (see Figure 2) this is probably due besides to coincidence, also to the booming economic cycle following the 2008 economic crisis. For this reason, it should be considered that test results from longer intervals should be regarded as normative.

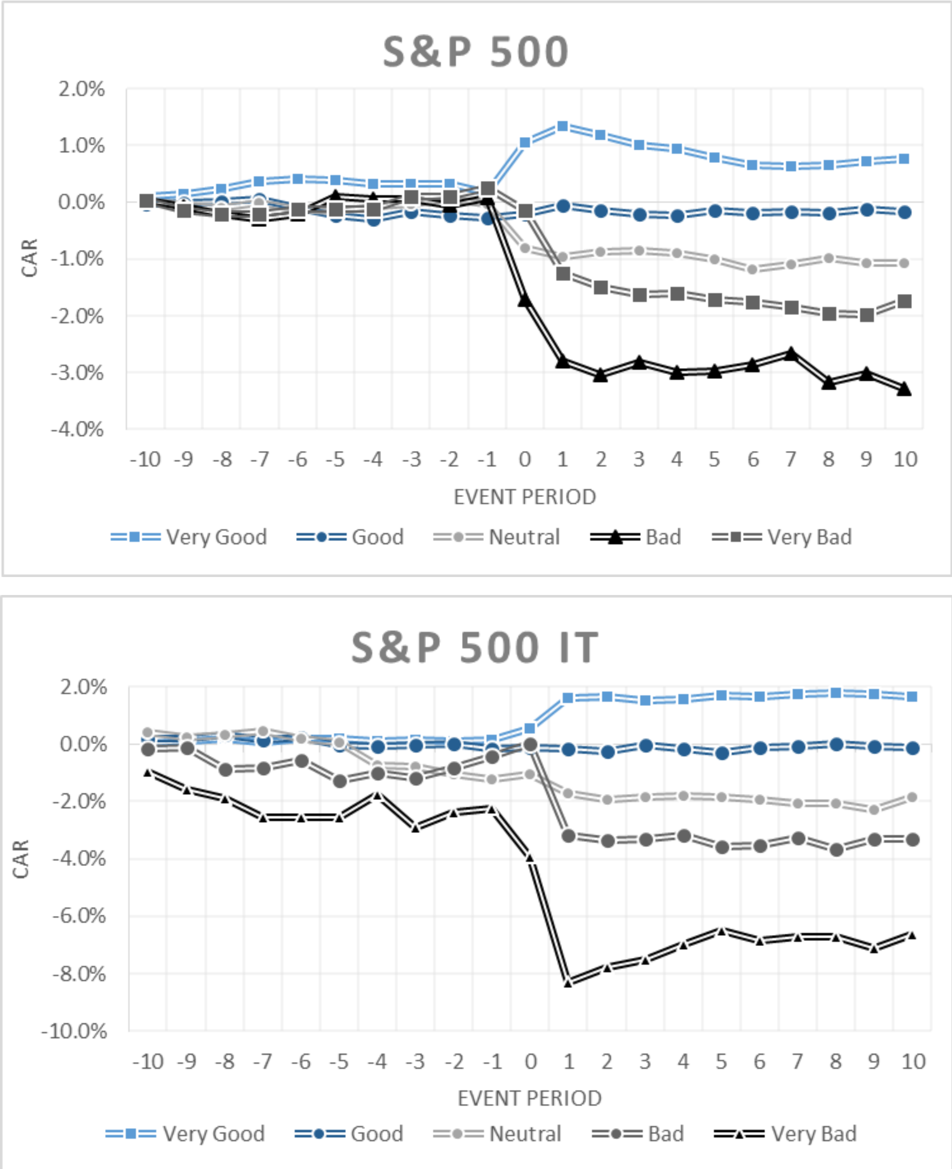


**Figure 3: The cumulative average abnormal returns of the five groups for the period around the event for the sample taken from the two stock indices for the very good, good, neutral, bad and very bad news groups.**

## Hypothesis testing and interpretation of results

Figure 3 presents spectacularly enough the average abnormal returns of the observation groups to give a more definitive picture of the conjectures made at the beginning of the research. Our hypotheses are partly confirmed and partly weakened by this picture. However, in order to determine whether significant phenomena can be observed, a statistical examination of the hypotheses is necessary. These can be found in the following two subchapters.

### 2.1.4. Price reactions caused by quarterly reports

This subsection contains an analysis of price reactions through the hypothesis test on the existence of abnormal returns. To find out whether these averages are really significantly different from zero, we carried out one-sample Student's t-tests. In all cases, the tested null-hypotheses and alternative hypotheses can be written as follows when examining the first hypothesis of the dissertation:

$$H_0:\ \theta = 0 \qquad\qquad H_1:\ \theta \neq 0 \ ,$$

where $\theta$ based on equation (13) is the test statistic defined as the ratio of cumulative abnormal return measured between $\tau_1$ and $\tau_2$ and of the associated standard deviation. The null-hypothesis thus assumes that the value so calculated is derived from a standard normal distribution. Based on economic intuition, we can expect to accept the null-hypothesis in the group of reports containing neutral news and, in case of positive and negative surprises to reject the null-hypothesis.

Tables 10 and 11 contain the $\overline{CAR}$ values and standard deviations from the samples of the S&P 500 and S&P 500 IT Index ($s$ indicates this standard deviation which is equal to the square root of the variance in equation (11)), as well as test statistics for the very good, good, neutral, bad and very bad groups at different intervals. We have already mentioned in chapter 1.2. that the estimation of the variance of the cumulative average abnormal returns is the error term-variances $\hat{\sigma}^2_{\varepsilon_i}$ calculated from the estimation period based on (2) according to equation (7). Because in equation (7), the square of the element number is in the denominator, it is clear that for groups with smaller number of elements we usually get higher variance, which increases the probability of accepting the null hypothesis.

description of the methodology, it was mentioned that the clustering of the dates of events causes a bias in the estimation of variance. Binder (1998) and Rao as well as Sreejith (2014) explain that this causes a relatively small problem in the absence of total clustering and the distribution of observations over time is relatively random. Judging by the nature of the event, quarterly reports generally fall within a generous one-month period. Some values do not fit into this pattern, as some companies' business years do not coincide with calendar years. However, total clustering is out of the question since the analysis spans 4 years and the reporting dates are spreading over a relatively wide interval even within a quarter.

Because we test the hypotheses with bilateral tests therefore $t_{0,975}$ denotes the critical values for the t-distribution at 95% significance level and $t_{0,995}$ for the 99% significance level. Obviously, these also differ between the groups, since the degree of freedom of tests is different (N-1) in each case. Because the distribution is symmetric, the critical values on the left correspond on the values on the right multiplied by minus 1, and are not shown separately in the table. Thus, using a 95% significance level for the test, for example, in the first line of Table 11, the acceptance range is a closed interval of -1.97 to 1.97.

An overview of the S&P 500 values shows that over the interval of the full event window (-10,10), we find significant cumulative abnormal returns for the very good, bad and very bad news, but for good news there is no significant cumulative abnormal return. In case of neutral news, however, the cumulative abnormal return of -1.08% is also significant. There is a positive relationship between the direction and level of cumulative abnormal returns and the direction and magnitude of the experienced surprise. At the same time, the market is shifting towards negative price reactions because, in the group of very good news, the cumulative abnormal return is 0.77%, while in case of good news it is -0.17% (although its value is not significantly different from 0), for neutral news -1.08%, for bad and very bad news -3.27% and -1.73%. Presumably, the significant price reactions experienced are due to the fact that in a trend that can be described by rising stock prices following the global economic shock of 2008, market participants' expectations of company reports are high and while they are responding to above-expectations news with modest price increases (conservatism Barberis et al. (1998)), in case of firms significantly below expectations, a more severe negative price reaction will develop (overconfidence, attribution theory Daniel, et al. (1998)). The negative abnormal return of the neutral news group may be explained by the fact that, with such heightened expectations, market participants even view EPS surprises in the +/- 1% range as negative news.

The difference experienced in the cumulative abnormal returns for the bad and very bad newsgroups is a somewhat surprising exchange in the ranking order compared to our expectations, as to the smaller surprise we find higher abnormal returns from the two newsgroups. This may be explained by the change in company EPS compared to the previous quarter or a year earlier EPS values. Or it may be that the market sentiment on the day of announcement matters. Quantifying these effects would be worth exploring in further research.

| S&P 500 | $\tau_1, \tau_2$ | *CAR* | *s* | $\theta$ | *Degree of freedom* | $t_{0.975}$ | $t_{0.995}$ | *p* |
|---|---|---|---|---|---|---|---|---|
| Very good news | -10 , 10 | 0.77% | 0.30% | 2.54 | 329 | 1.97 | 2.59 | 0.0114 |
| | -10 -1 | 0.17% | 0.21% | 0.84 | 329 | 1.97 | 2.59 | 0.4037 |
| | 0 , 10 | 0.60% | 0.22% | 2.72 | 329 | 1.97 | 2.59 | 0.0069 |
| | 0 , 1 | 1.17% | 0.09% | 12.55 | 329 | 1.97 | 2.59 | 0.0000 |
| | 2 , 10 | -0.58% | 0.20% | -2.91 | 329 | 1.97 | 2.59 | 0.0038 |
| Good news | -10 , 10 | -0.17% | 0.33% | -0.53 | 205 | 1.97 | 2.60 | 0.5952 |
| | -10 -1 | -0.28% | 0.22% | -1.27 | 205 | 1.97 | 2.60 | 0.2073 |
| | 0 , 10 | 0.11% | 0.24% | 0.47 | 205 | 1.97 | 2.60 | 0.6382 |
| | 0 , 1 | 0.23% | 0.10% | 2.29 | 205 | 1.97 | 2.60 | 0.0231 |
| | 2 , 10 | -0.12% | 0.21% | -0.56 | 205 | 1.97 | 2.60 | 0.5771 |
| Neutral news | -10 , 10 | -1.08% | 0.51% | -2.13 | 90 | 1.97 | 2.63 | 0.0357 |
| | -10 -1 | -0.04% | 0.35% | -0.11 | 90 | 1.97 | 2.63 | 0.9133 |
| | 0 , 10 | -1.04% | 0.37% | -2.84 | 90 | 1.97 | 2.63 | 0.0055 |
| | 0 , 1 | -0.91% | 0.16% | -5.87 | 90 | 1.97 | 2.63 | 0.0000 |
| | 2 , 10 | -0.12% | 0.33% | -0.38 | 90 | 1.97 | 2.63 | 0.7071 |
| Bad news | -10 , 10 | -3.27% | 0.92% | -3.54 | 29 | 1.97 | 2.76 | 0.0014 |
| | -10 -1 | 0.08% | 0.64% | 0.13 | 29 | 1.97 | 2.76 | 0.8984 |
| | 0 , 10 | -3.36% | 0.67% | -5.02 | 29 | 1.97 | 2.76 | 0.0000 |
| | 0 , 1 | -2.89% | 0.29% | -10.12 | 29 | 1.97 | 2.76 | 0.0000 |
| | 2 , 10 | -0.47% | 0.61% | -0.78 | 29 | 1.97 | 2.76 | 0.4444 |
| Very bad news | -10 , 10 | -1.73% | 0.68% | -2.54 | 62 | 1.99 | 2.66 | 0.0136 |
| | -10 -1 | 0.26% | 0.47% | 0.55 | 62 | 1.99 | 2.66 | 0.5825 |
| | 0 , 10 | -1.99% | 0.49% | -4.04 | 62 | 1.99 | 2.66 | 0.0002 |
| | 0 , 1 | -1.51% | 0.21% | -7.19 | 62 | 1.99 | 2.66 | 0.0000 |
| | 2 , 10 | -0.48% | 0.45% | -1.07 | 62 | 1.99 | 2.66 | 0.2878 |

**Table 11: Cumulative average abnormal returns on a sample from the S&P 500 index and standard deviations of these returns, test statistics, critical values, and p values in case of the five newsgroups and various time intervals.**

At the 11-day (0,10) interval from the date of publication of the quarterly report, higher t-statistics are obtained, that is, in this interval, except for the good news group, the cumulative abnormal return differs significantly from 0 at each standard significance level.

At the interval of 10 days (-10, -1) prior to reporting, we get an answer to see if there is a leak of insider information that leaves a trace in the form of abnormal returns. This claim can be rejected for each category, since no cumulative abnormal returns significantly different to 0 are found in this interval.

In the interval (0,1), abnormal returns whose direction corresponds to expectations and that are significant are found in each group, although cumulative abnormal returns are also significant and negative in the neutral news group.

Examining the period (2, 10), we can determine whether there is a momentum on the trading days following the event. Based on the results, we can see significant abnormal returns and thus a trend in the very good news group over this time period, but its direction is opposite to the announcement, meaning a significant price correction and not a trend developing due to the announcement that we can observe. In case of good, neutral, bad and very bad news at all usual significance levels, the existence of the developed moment can clearly be rejected.

Examining the S&P 500 IT Sample Chart gives similar results (Table 12). For the interval (-10,10), similarly to the S&P 500 index, we see significant cumulative abnormal returns in the very good, neutral, bad and very bad newsgroups, while in the good news there is no significant return. The level of cumulative abnormal returns is higher than that seen in the S&P 500 index for very good news, neutral news and very bad news, while it is approximately the same for good and bad news. In contrast to the S&P 500 index, the cumulative abnormal return of very bad news is higher than that of the bad news group. There is an even more positive relationship between the level and direction of the cumulative abnormal return and the magnitude of the surprise: the direction of the surprise generally determines the direction of the cumulative abnormal returns, the greater the magnitude of the surprise, the greater the experienced cumulative abnormal return. Here, too, there is a shift towards negative price reactions among newsgroups: 1.63% cumulative abnormal returns for very good news, virtually no movement for good news, the detected -0.11% is not significantly different from 0, the extent of the cumulative abnormal returns is -1.86% for neutral news, while -3.3% and -6.63% for bad and very bad news.

In case of the 11-day (0,10) interval from the date of publication of the quarterly report, the abnormal return is significant for the very good news, bad and very bad news, and insignificant for good news similarly to that seen in the S&P 500 index, however it is no longer significant here for the neutral newsgroup.

On the interval (0,1), we see significant cumulative abnormal returns in each group, similar to the S&P 500 index, except for the good news group, where there is no significant cumulative abnormal return on this interval.

| S&P 500 IT | $\tau_1, \tau_2$ | CAR | s | $\theta$ | Degree of freedom | $t_{0.975}$ | $t_{0.995}$ | p |
|---|---|---|---|---|---|---|---|---|
| Very good news | -10 , 10 | 1.63% | 0.33% | 4.95 | 410 | 1.97 | 2.59 | 0.0000 |
| | -10 -1 | 0.16% | 0.23% | 0.69 | 410 | 1.97 | 2.59 | 0.4895 |
| | 0 , 10 | 1.48% | 0.24% | 6.18 | 410 | 1.97 | 2.59 | 0.0000 |
| | 0 , 1 | 1.44% | 0.10% | 14.13 | 410 | 1.97 | 2.59 | 0.0000 |
| | 2 , 10 | 0.04% | 0.22% | 0.17 | 410 | 1.97 | 2.59 | 0.8661 |
| Good news | -10 , 10 | -0.11% | 0.47% | -0.22 | 192 | 1.97 | 2.60 | 0.8235 |
| | -10 -1 | -0.15% | 0.32% | -0.45 | 192 | 1.97 | 2.60 | 0.6512 |
| | 0 , 10 | 0.04% | 0.34% | 0.12 | 192 | 1.97 | 2.60 | 0.9022 |
| | 0 , 1 | -0.01% | 0.15% | -0.07 | 192 | 1.97 | 2.60 | 0.9405 |
| | 2 , 10 | 0.05% | 0.31% | 0.17 | 192 | 1.97 | 2.60 | 0.8642 |
| Neutral news | -10 , 10 | -1.86% | 0.70% | -2.65 | 74 | 1.99 | 2.64 | 0.0098 |
| | -10 -1 | -1.25% | 0.48% | -2.57 | 74 | 1.99 | 2.64 | 0.0121 |
| | 0 , 10 | -0.62% | 0.51% | -1.21 | 74 | 1.99 | 2.64 | 0.2298 |
| | 0 , 1 | -0.45% | 0.22% | -2.07 | 74 | 1.99 | 2.64 | 0.0418 |
| | 2 , 10 | -0.17% | 0.46% | -0.36 | 74 | 1.99 | 2.64 | 0.7183 |
| Bad news | -10 , 10 | -3.30% | 1.20% | -2.74 | 25 | 2.06 | 2.79 | 0.0111 |
| | -10 -1 | -0.44% | 0.83% | -0.53 | 25 | 2.06 | 2.79 | 0.6035 |
| | 0 , 10 | -2.86% | 0.87% | -3.29 | 25 | 2.06 | 2.79 | 0.0030 |
| | 0 , 1 | -2.75% | 0.37% | -7.39 | 25 | 2.06 | 2.79 | 0.0000 |
| | 2 , 10 | -0.12% | 0.79% | -0.15 | 25 | 2.06 | 2.79 | 0.8837 |
| Very bad news | -10 , 10 | -6.63% | 1.60% | -4.15 | 14 | 2.14 | 2.98 | 0.0010 |
| | -10 -1 | -2.26% | 1.10% | -2.05 | 14 | 2.14 | 2.98 | 0.0597 |
| | 0 , 10 | -4.37% | 1.16% | -3.78 | 14 | 2.14 | 2.98 | 0.0020 |
| | 0 , 1 | -6.03% | 0.49% | -12.24 | 14 | 2.14 | 2.98 | 0.0000 |
| | 2 , 10 | 1.66% | 1.05% | 1.59 | 14 | 2.14 | 2.98 | 0.1339 |

**Table 12: Cumulative average abnormal returns of the S&P 500 IT index, standard deviations of these returns, test statistics, critical values, and p values for the five newsgroups and for different time intervals.**

In the 10-day (-10, -1) interval preceding the reports, only the neutral news group shows significant abnormal returns. The period after the rapid price reaction following company reports over the interval (2,10) shows no significant abnormal returns, meaning no trend in the days following the report develops (as opposed to the S&P 500, there is no price correction here in the very good news group).

Summarizing the presented results:

- For the S&P 500 and S&P 500 IT indexes, we can find significant cumulative abnormal returns over the entire event window (-10,10) for very good, bad, neutral and very bad news, but for good news there is no significant cumulative abnormal return. There is a positive relationship between the direction and level of cumulative abnormal returns and the experienced direction and magnitude of the surprise with a shift towards negative price reactions, while in case of the very good news of the S&P 500 cumulative abnormal return is + 0.77, the neutral news is already associated with a negative cumulative abnormal return of -1.08%, bad and very bad newsgroups with -3.27% and -1.73%. Presumably, the experienced significant price reactions are due to the fact, that market participants' expectations of corporate reports are high in a trend, which is characterized by rising stock prices following the global economic shock of 2008, and even EPS-surprises in the +/- 1% range are considered as negative news. For the S&P 500 IT index, the level of cumulative abnormal returns is higher than for the S&P 500 index for very good news, neutral news and very bad news, while it is approximately the same for good and bad news.
- In the interval (0, 1), significant cumulative abnormal returns corresponding to the direction of surprise are found for both indices and in each newsgroup. In case of neutral news negative returns due to investor disappointment are also present in this range, with the exception of the good newsgroup of the S&P 500 IT index where the cumulative abnormal return is not significantly different from 0.
- In the period following the immediate and significant price response at the release of corporate results, on the interval (2.10), shows significant cumulative abnormal returns only in the very good news group of the S&P 500 index, but its direction is opposite to that of the announcement. That is, it is a significant

price correction what we can observe and not a trend caused by the announcement. In contrast, for the S&P 500 neutral and bad newsgroups and each group of S&P500 IT index significant abnormal returns cannot be found over this time period, so new information is almost fully embedded already on the day after the announcement. Thus, all in all the analysis confirms that the market for stocks in the selected sample is moderately efficient.

- <u>The first statement of the hypothesis 1 is accepted:</u>
- The direction and magnitude of corporate profitability surprises determine how stock prices change as a result of the announcement. At the same time, a shift can be observed in the level and direction of cumulative abnormal returns perceived for each newsgroup to negative price reactions, since a significant positive return occurs only in the very good newsgroup, whereas the good newsgroup no longer has significantly different return from 0. We can see already negative cumulative abnormal returns in the neutral news group, but in the bad and very bad news group its magnitude exceeds that of experienced in the neutral group.

  <u>The second statement of the hypothesis 1 is rejected:</u> the effect of the new information can no longer be observed on the trading days following the announcement and there is no trend forming corresponding to the direction of surprise.

### 2.1.5. Differences in the effect of the EPS surprise

This subchapter contains tests of our second hypothesis. According to this hypothesis, the cumulative average abnormal returns observed in the technology sector as a result of surprise are not the same as the values of the other sample, and the deviation from zero is greater in case of technology equities. We based this assumption on that valuation of companies in the industry is likely to be more uncertain, so that the stock market price may temporarily deviate from its reasonable fair value, and EPS fact data are likely to deviate more from analyst consensus.

A two-sample *t*-test can be used to test whether the cumulative mean abnormal returns in the two sample newsgroups differ significantly from each other. We performed the methodological details of the two independent sample tests and the calculations of our test statistics on the basis of Hunyadi and Vita's (2008) book (Chapter 7).

The variances of the two samples were statistically different, so the two-sample t-test can be applied to the cumulative abnormal returns over the interval (-10,10). In this case we examine the following pair of hypotheses:

$$H_0:\ \overline{CAR}_{SP}(-10,10) = \overline{CAR}_{SPIT}(-10,10)\ ,$$
$$H_1:\ \overline{CAR}_{SP}(-10,10) \neq \overline{CAR}_{SPIT}(-10,10)\ ,$$

where the sub-indices refer to a sample taken from the stock index in question, and in this case, we also compare the categories of positive and negative EPS reports in pairs. In this case, the t-statistics can be calculated using the following formula:

$$t = \frac{\overline{CAR}_{SP}(-10,10) - \overline{CAR}_{SPIT}(-10,10)}{\sqrt{s_{SP}^2/N_{SP} + s_{SPIT}^2/N_{SPIT}}}\ ,$$

where $N_{SP}$ and $N_{SPIT}$ are the number of items in the examined category of the corresponding indices.

| | *t-stat* | *Degree of freedom* | $t_{0,975}$ | $t_{0,995}$ | *p* |
|---|---|---|---|---|---|
| Very Good | -37.08 | 726.1 | -1.96 | 1.96 | 0.0000 |
| Good | -1.66 | 338.6 | -1.97 | 1.97 | 0.0971 |
| Neutral | 8.09 | 131.1 | -1.98 | 1.98 | 0.0000 |
| Bad | 0.10 | 46.6 | -2.01 | 2.01 | 0.9234 |
| Very Bad | 11.63 | 15.2 | -2.13 | 2.13 | 0.0000 |

**Table 13: Difference between cumulative average abnormal returns on samples from the S&P 500 and S&P 500 IT index and t-statistics for the five newsgroups in the interval (-10,10).**

Based on the *t*-statistics in Table 13, the null-hypothesis is rejected. There is a significant difference between the cumulative abnormal returns of the S&P 500 and S&P 500 IT indices around quarterly reports in the very good, very bad and neutral newsgroups at the usual significance levels and S&P 500 IT newsgroups have higher cumulative abnormal returns of the two indices. In the group of good and bad news, there is no significant difference in the amount of abnormal returns experienced between the two indices. In case of the good news group, this is not a surprising development given that in both cases we saw not significantly different returns from 0 in the earlier part of the analysis in this newsgroup, and considering that due to the shift towards negative price reactions this news group can be reckoned as the reference point among news groups. We have no explanation for the level-match of cumulative abnormal returns found in the bad news group. Based on the results, we generally agree with hypothesis 2 formulated in the chapter that the impact of surprise on prices is stronger in the technology sector compared to the general stock market.

## 2.2. ANALYSING THE RETURNS OF HUNGARIAN ABSOLUTE RETURN MUTUAL FUNDS WITH THE HELP OF MPPM AND DETECTION OF TRACES OF RETURN MANIPULATION

In this chapter we present the evaluation of absolute return funds in Hungary and the detection of traces of return manipulation through our own calculations as a new result, as we do not know any example of tracing of return manipulation in the literature for Hungarian investment funds. Writings in this chapter used up a lot from our true articles, (Rácz 2019a, 2019b)

The following new results were obtained from our analysis:

1) We have compared the results of the Sharpe ratio with the results of MPPM and based on the rank-correlation, we showed some traces of return manipulation.
2) As a new result, we presented the value and ranking differences between the various MPPM versions and their possible causes.
3) As an innovation, we recommend the application of the MPPM version of Ingersoll et al. (2007) because of its accuracy, instead of the version by Brown et al. (2010) for both performance evaluation and the calculation of the Doubt Ratio.
4) We have analysed the signalling ability of the MPPM-based Doubt Ratio in revealing return manipulation or suboptimal investment decisions, and its relationship to alternative methods for Bias Ratio and discontinuity analysis.
    i. Contrary to the close overlap of the Doubt Ratio with other return manipulation detecting methods (80% match according to Brown et al. (2010)), our analysed sample showed mixed results, as alternative methods indicated anomalies in 10 out of 31 investment funds, that is, return manipulation with high probability, while the Doubt Ratio flagged only 4 investment funds as suspicious. We found signs of

discontinuity too around 0 in risk adjusted returns for the former in 4 cases, while for the later in 1 occasion.

ii. Overall, therefore, according to our results, the Bias Ratio has proved to be a better pre-screening tool for more detailed analysis of return manipulation (e.g. with discontinuity analysis) than the Doubt Ratio

iii. Based on investment policies and interviews with investment managers, only in case of one fund, the Concorde Citadella seem suspicious signals well founded, and this fund was marked as suspicious by both the Doubt Ratio and the Bias Ratio. In case of this fund, the existence of distortion due to sometimes sub-optimal investment decisions seems well founded in the knowledge of investment policy.

### 2.2.1. Treatment of items needed to perform the analysis

In this subchapter we describe how to handle the elements needed for analysis as well as the steps to calculate MPPM using the formula by Ingersoll et al. (2007) and by Brown et al. (2010)

31 investment funds were picked for the analysis (see Table 14) that are in the category of absolute return investment funds, denominated in HUF, public, open-end, has at least 7 years of continuous trading history and their return data is available from BAMOSZ (Hungarian Association of Investment Fund and Asset Managers) website[6]. For the analysis period, we chose April 28, 2010 and April 27, 2017 which included 55,056 daily returns

[6] http://www.bamosz.hu/

| Nr. | Name of the fund | ISIN code of the fund |
|---|---|---|
| 1 | Aberdeen Diversified Growth Alapok Alapja I | HU0000704556 |
| 2 | AEGON Alfa | HU0000703970 |
| 3 | Aegon MoneyMaxx A | HU0000703145 |
| 4 | Aegon ÓzonMaxx | HU0000705157 |
| 5 | AEGON Smart Money | HU0000708169 |
| 6 | Budapest Kontroll Alap A | HU0000702741 |
| 7 | Citadella Származtatott | HU0000707948 |
| 8 | Concorde Columbus | HU0000705702 |
| 9 | Concorde PB2 | HU0000704705 |
| 10 | Concorde Rubicon | HU0000707252 |
| 11 | Concorde VM | HU0000703749 |
| 12 | Erste DPM Alternativ | HU0000705314 |
| 13 | Erste Multistrategy Abszolút Hozamú Alapok Alapja | HU0000705322 |
| 14 | Generali IPO | HU0000706791 |
| 15 | Generali Spirit | HU0000706833 |
| 16 | Generali Titanium Abszolút Alapok Alapja | HU0000706817 |
| 17 | OTP Abszolút Hozam A | HU0000704457 |
| 18 | OTP EMDA | HU0000706361 |
| 19 | OTP G10 Euro A | HU0000706221 |
| 20 | OTP Supra | HU0000706379 |
| 21 | OTP Új Európa Alap A | HU0000705827 |
| 22 | Platina Alfa | HU0000704648 |
| 23 | Platina Beta | HU0000704655 |
| 24 | Platina Delta A | HU0000704671 |
| 25 | Platina Gamma | HU0000704663 |
| 26 | Platina Pí A | HU0000704689 |
| 27 | Raiffeisen Hozam Prémium Alap A | HU0000703699 |
| 28 | Raiffeisen Index Premium | HU0000703707 |
| 29 | Raiffeisen Private Pannonia Alapok Alapja A | HU0000705231 |
| 30 | Sovereign PB Származtatott | HU0000707732 |
| 31 | Takarek Invest Abszolút Hozamú Alap | HU0000707997 |

**Table 14: Selected Absolute Return Funds.**

## Treatment of the risk-free rate ($r_{ft}$)

For risk-free return, we used the evolution of reference rate of the RMAX index as this short-term government bond rate is not only considered risk-free but also reflects the material changes in risk-free returns over the analysis period and is considered by most of the analysed investment funds in the sample as risk-free reference rate. For the Sharpe ratio, we used the average return calculated for the entire period, which returned an annualized 4.67%. Daily changes in the reference rate of the RMAX index were taken into account in calculating the MPPM. For the purpose of calculating the daily risk-free rate calculated on a continuous basis over a given period, the RMAX index shall be scaled from the annualized reference rate to the daily rate based on the following 250 trading days according to the following formula: To calculate the daily continuously compounded risk-free rate for the given period, one has to prorate the annualized reference rate of the RMAX Index to daily return, calculating with 250 trading days, according to the following formula:

$$r_{ft(continuous)} = \frac{ln\left(\frac{1+r_{ft}}{1}\right)}{250} \quad .$$

## Treatment of the fund returns ($r_t$)

The daily log returns can be determined by downloading the daily unit price data from the BAMOSZ website and using the following formula

$$r_t = ln\left(\frac{P_t}{P_{t-1}}\right) \quad .$$

## Determining MPPM values with the Ingersoll et al. (2007) formula

The Ingersoll MPPM values need to be determined for ρ = 2, ρ = 3 and ρ = 4. In all three cases, first the return premium from the given period over the risk-free rate should be raised to the power of 1 – ρ to adjust the return ratio by the risk:

$$\text{Risk adjusted return premium} = \left(\frac{1 + r_t}{1 + r_{ft}}\right)^{1-\rho} \quad .$$

then the log of the average risk-adjusted return premium calculated for the whole period is divided by 1 – ρ:

$$\frac{1}{(1-\rho)} ln\left(\frac{1}{T}\sum_{t=1}^{T} \text{Risk adjusted return premium}_\text{t}\right)$$

Finally, the value of $\hat{\Theta}$ calculated for the daily returns is annualised by multiplying it for 250 trading days.

$$\hat{\Theta}_{Ingersoll} = \frac{1}{\Delta t}\hat{\Theta}_{napi} \quad .$$

$\hat{\Theta}$ estimates the risk-adjusted return premium of the investment fund. In other words, a given $\hat{\Theta}$ is the portfolio's score that equals the continuously compounded and annualised return of a risk-free asset, exceeding the risk-free rate by $\hat{\Theta}$.

## Determining MPPM values with the Brown et al. (2010) formula

In the Brown et al. (2010) approach, the MPPM can be stated as the difference between the average excess return and the variance of the excess return calculated from the sample, where the coefficient of the variance is (1 – ρ)/2.:

$$\hat{\Theta}(\rho) = \frac{1}{\Delta t}\left[\bar{x} + \frac{1-\rho}{2}(s_x^*)^2\right] \quad . \qquad (15)$$

Thus, to calculate the Brown et al. (2010) MPPM, one first needs to calculate the average excess return by taking the log of the ratio of the daily return of the investment fund and the risk-free rate for each day.

$$\text{Return premium} = \ln\left(\frac{1 + r_t}{1 + r_{ft}}\right) \quad .$$

then their average is calculated for the whole period:

$$\bar{x} = \frac{1}{T}\sum_{t=1}^{T} \text{Return premium}_t \quad .$$

In the Brown approach, the other building block is the calculation of the variance of the excess return calculated from the sample.

Finally, the difference between the two values is calculated for the three ρ-s (2, 3 and 4), where the coefficient of variation is (1 – ρ)/2. The daily $\hat{\Theta}$ value derived in this manner is prorated for annualised return by multiplying it by 250 trading days

$$\hat{\Theta}_{Brown} = \frac{1}{\Delta t}\hat{\Theta}_{napi} \quad .$$

.

### 2.2.2. Comparison of the ranking of the Sharpe-ratio and of the Ingersoll et al. (2007) MPPM

In this subchapter, we look for signs of return manipulation using the differences in rank-correlation values relative to Sharpe Ratio as a *classical* measure. We compared Sharpe-ratios to MPPMs calculated with various risk aversion factors. Rank-correlations have relatively high values in the interval 0.76-0.82, which is higher than the values around 0.7 seen in international examples, but still indicates as much difference to the classical measure that might be caused by some level of return manipulation or return smoothing

Rank-correlation values indicate that there are some funds where there is a significant difference between the Sharpe ratio and MPPM ranking, especially with risk aversion factor 4 (MPPM(4)):

- OTP G10 Euro is thirteenth based on the Sharpe-ratio, but only thirty-one ranked by MPPM(4),
- Platina Delta is fourteenth in the Sharpe-ratio, but only twenty-ninth in the MPPM(4) ranking,
- Raiffeisen Index Premium is twenty-eighth in the Sharpe-based ranking, but twenty-one according to MPPM (4)
- Raiffeisen Hozam Premium is ranked 29th in Sharpe rank, but eighteenth in rank in MPPM(4).
-

| | |
|---|---|
| Sharpe-MBTM(2) | 0.8202 |
| Sharpe-MBTM(3) | 0.8024 |
| Sharpe-MBTM(4) | 0.7617 |

**Table 15: Rang-correlations between the Sharpe-ratio and the MPPM for different risk aversion factors.**

## Evaluation of five investment funds ranked best and worst based on the MPPM calculated with the risk aversion factor (3)

Analyzing best and worst ranked investment funds according to MPPM, we can see that MPPM rankings can be considered stable because they give almost the same results for the different risk aversion factors – the rank-correlation, between MPPM versions with different risk aversion factors shows very high values in the range of 0.97-0.99. As shown in Table 16, the Sharpe Ratio and MPPM based rankings show a larger difference for the worst rated MPPM(3) funds than for the MPPM(3) best rated funds. This is mainly due to the OTP G10 Euro fund because as shown in Figure 4, according to the Sharpe-ratio it is thirteenth in the line, while according to MPPM(3) it is only thirty-first.

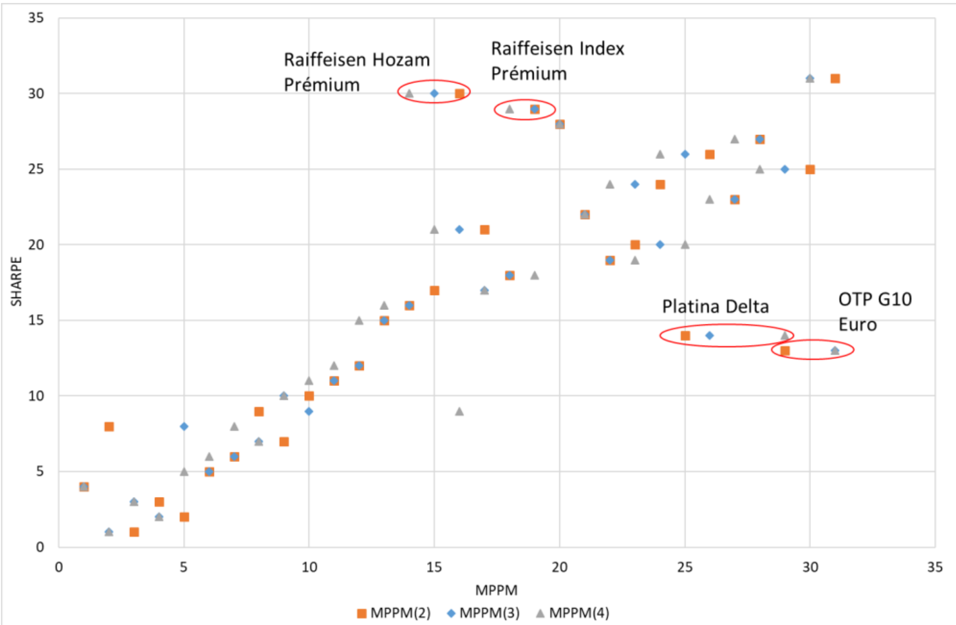


**Figure 4: Comparison of the ranking of the Sharpe-ratio and the MPPM with different risk aversion factors.**

Citadella Származtatott, Platina Pi, Platina Alpha are second, third, and fourth respectively according to MPPM, and first, third and second according to Sharpe-ratio. At the same time, it is interesting to see that these investment funds are members of the group under review of top-5 funds with the highest Doubt Ratio values. Although the highest Doubt Ratios for the funds under review are in the 30-50 band, which does not count as outstanding at all, but it it can be seen that MPPM does not change significantly for different risk aversion factors in case of some funds, i.e. the implicit risk aversion factor is relatively high. .

Concorde Rubicon is ranked first calculated by MPPM with a risk aversion factor (3), and fourth by the Sharpe-ratio, while OTP Supra is fifth in the MPPM and eighth in the Sharpe-ratio. According to Brown et al. (2010) MPPM is the difference of the average return and the variance of the excess return, so it punishes standard deviation less than the Sharpe-ratio. Concorde Rubicon and OTP Supra are all ranked in the top five in MPPM rankings, though they have one of the highest standard deviations in the examined sample (the twenty-fourth and twenty-eighth least secure of the 31 investment funds, meaning there are only seven and three funds with even higher standard deviation).

| **Best 5 funds based on MBTM(3)** | **Concorde Rubicon** | **Citadella** | **Platina Pí** | **Platina Alfa** | **OTP Supra** |
|---|---|---|---|---|---|
| Average return | 10.84 | 4.00 | 9.40 | 9.21 | 13.36 |
| Average return rankin | 3 | 4 | 5 | 6 | 2 |
| Standard deviation of returns | 7.39 | 4.47 | 4.67 | 4.19 | 15.19 |
| Standard deviation of returns ranking | 24 | 12 | 14 | 10 | 28 |
| Sharpe-ratio | 0.84 | 1.10 | 1.01 | 1.08 | 0.57 |
| Sharpe-ratio ranking | 4 | 1 | 3 | 2 | 8 |
| MBTM(2) | 0.0549 | 0.0477 | 0.0454 | 0.0441 | 0.0513 |
| MBTM(3) | 0.0522 | 0.0467 | 0.0443 | 0.0432 | 0.0386 |
| MBTM(4) | 0.0495 | 0.0457 | 0.0432 | 0.0424 | 0.0259 |
| Doubt Ratio | 22.16 | 49.81 | 43.68 | 52.43 | 6.04 |
| Doubt Ratio ranking | 26 | 30 | 28 | 31 | 21 |
| MBTM(2) ranking | 1 | 3 | 4 | 5 | 2 |
| MBTM(3) ranking | 1 | 2 | 3 | 4 | 5 |
| MBTM(4) ranking | 1 | 2 | 3 | 4 | 7 |
| **Worst 5 funds based on MBTM(3)** | **OTP G10 Euro** | **Sovereign PB** | **Generali Spirit** | **ERSTE Multistrateg** | **Generali Titanium** |
| Average return | 7.03 | -1.17 | 0.45 | 0.79 | 1.33 |
| Average return rankin | 9 | 31 | 30 | 29 | 28 |
| Standard deviation of returns | 22.07 | 5.76 | 6.95 | 5.60 | 6.96 |
| Standard deviation of returns ranking | 31 | 17 | 21 | 16 | 22 |
| Sharpe-ratio | 0.11 | -1.01 | -0.61 | -0.69 | -0.48 |
| Sharpe-ratio ranking | 13 | 31 | 25 | 27 | 23 |
| MBTM(2) | -0.0477 | -0.0625 | -0.0481 | -0.0421 | -0.0393 |
| MBTM(3) | -0.0719 | -0.0644 | -0.0505 | -0.0437 | -0.0418 |
| MBTM(4) | -0.0961 | -0.0663 | -0.0529 | -0.0453 | -0.0443 |
| Doubt Ratio | 0.03 | -30.76 | -17.66 | -24.79 | -13.99 |
| Doubt Ratio ranking | 17 | 4 | 8 | 6 | 9 |
| MBTM(2) ranking | 29 | 31 | 30 | 28 | 27 |
| MBTM(3) ranking | 31 | 30 | 29 | 28 | 27 |
| MBTM(4) ranking | 31 | 30 | 28 | 27 | 26 |

**Table 16: Properties of funds ranked best and worst by MPPM.**

### 2.2.3. Detection of traces of return manipulation and smoothing by different methods

In this suchapter, we look for traces of return manipulation, return smoothing, or suboptimal investment decisions using a variety of methods, using the Doubt Ratio, Bias Ratio, and discontinuity analysis to filter out investment funds that are most likely to have them.

#### Analysis of investment funds with high Doubt Ratio

With the help of the Doubt Ratio and the Sharpe Ratio, we identify a group of investment funds - by their difference from the group average - that are most likely to be "suspected" with return manipulation or distortion due to suboptimal investment decisions. Brown et al. (2010) suggest that a Doubt Ratio value of about 150 is a sign of potential performance manipulation in return smoothing or suboptimal investment decisions. The 5 highest Doubt Ratioa are shown in Table 17:

- Platina Alfa,
- Citadella Származtatott,
- Platina Béta,
- Platina Pí,
- Concorde Columbus.

The Doubt Ratio remains in the 30-50 band even for these funds, which is far below the suspicious indication of around 150, so we have not found a clear track record for return manipulation or suboptimal investment decisions based on this method.

| | Platina Alfa | Citadella | Platina Béta | Platina Pí | Concorde Columbus |
|---|---|---|---|---|---|
| Average return | 9.21 | 9.61 | 6.46 | 9.40 | 8.93 |
| Average return rankin | 6 | 4 | 11 | 5 | 7 |
| Standard deviation of returns | 4.19 | 4.47 | 2.78 | 4.67 | 5.30 |
| Standard deviation of returns ranking | 10 | 12 | 6 | 14 | 15 |
| Sharpe-ratio | 1.08 | 1.10 | 0.65 | 1.01 | 0.80 |
| Sharpe-ratio ranking | 2 | 1 | 7 | 3 | 5 |
| MBTM(2) | 0.04412 | 0.04774 | 0.01818 | 0.04537 | 0.03981 |
| MBTM(3) | 0.04324 | 0.04674 | 0.01779 | 0.04429 | 0.03841 |
| MBTM(4) | 0.04237 | 0.04574 | 0.01740 | 0.04320 | 0.03701 |
| Doubt Ratio | 52.43 | 49.81 | 49.18 | 43.68 | 30.44 |
| Doubt Ratio ranking | 31 | 30 | 29 | 28 | 27 |
| MBTM(2) ranking | 5 | 3 | 9 | 4 | 6 |
| MBTM(3) ranking | 4 | 2 | 8 | 3 | 6 |
| MBTM(4) ranking | 4 | 2 | 8 | 3 | 5 |

**Table 17: Properties of funds with the highest Doubt Ratio.**

Interestingly enough, four of the funds with the highest 5 Doubt Ratio are also the 7 funds with the highest Sharpe Ratio and are among the top 8 funds by MPPM. With all this in mind, we cannot claim that return manipulation or suboptimal investment decisions would result in the excellent Sharpe-ratio performance and ranking of these five funds.

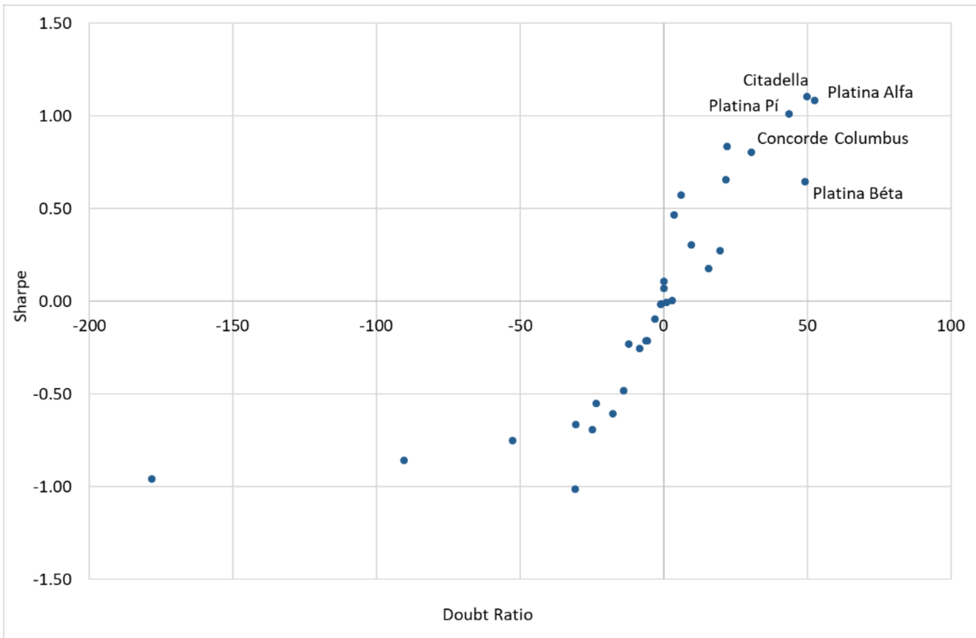


**Figure 5: Analysis of funds with the highest Doubt Ratios.**

However, in the Sharpe-Ratio-Doubt Ratio space (see Table 5), these 5 investment funds appear to be outliers with their extreme values compared to other observed investment funds, so at least caution and further investigation are recommandable

## Detection of return manipulation with the help of the Bias Ratio

As an alternative technique, we have also calculated Bias Ratios to provide a more reliable view of investment funds that may show distortions due to return smoothing, return manipulation or other suboptimal investment decisions. Since the analysed investment funds basically want to outperform the RMAX-return which is considered risk-free, and many of them may hold their investments in risk-free bonds until available investment opportunities, it is a legitimate assumption that there is not a chance to discover anomalies around the exceeding of the 0% return, but around the current returns of the RMAX index (since most of our analised funds regard the return of this index as benchmark). In addition, Abdulali (2006) points out that the use of the Bias Ratio is less reliable for investment funds or hedge funds with high cash investments. Accordingly, the Bias Ratio values were calculated on periodically adjusted returns (as the RMAX index periodic returns also fluctuate) with the risk-free rate (as a substitute for that with the RMAX index). In addition, calculations were made for returns reduced by risk-free rates and increased by TER (Total Expense Ratio). However, there was no significant difference between the two corrections calculated in terms of rank and conclusions, so we will present below the values of the Bias Ratio calculated for returns corrected with the RMAX index returns and the interpretation of the results.

The Bias Ratio values are largely concentrated between 1.047 and 1.29 quartiles (see Figure 6). The avarage is 1.23, while the median is 1.165, the lowest is 0.895, and the highest is 2.4.

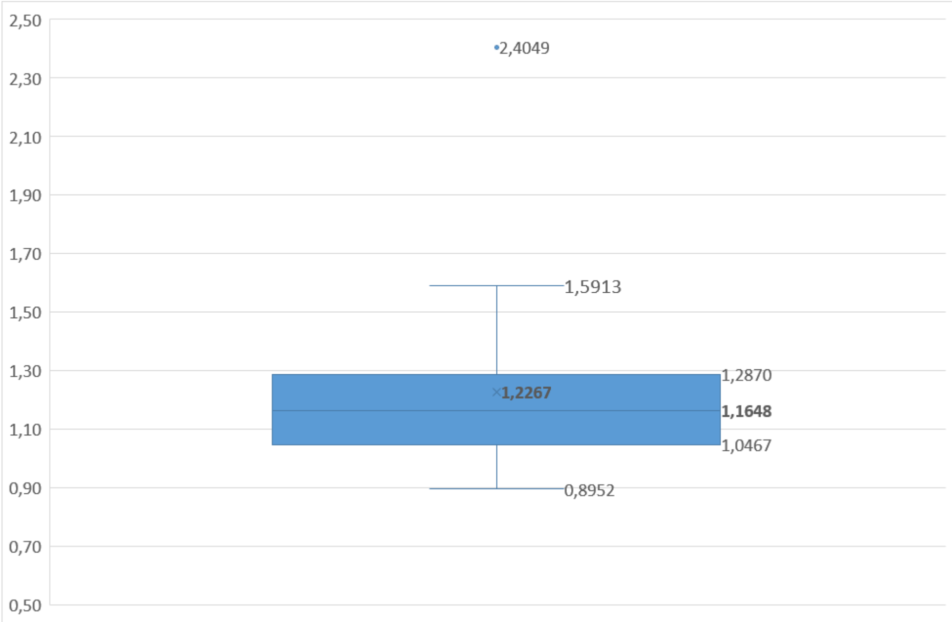


**Figure 6: Distribution of the Bias Ratio for the investment funds under investigation.**

According to Abdulali (2006), it is worth using the Doubt Ratio as an indicator of possible return smoothing or manipulation by examining in more detail those investment funds or hedge funds that are above the median value of the Doubt Ratio of the group of funds belonging to given type of funds. Thus, strictly following the recommendations of Abdulali (2006), it would be worthwhile to investigate further 10 investment funds based on the median, and 15 based on the average for traces of biases due to return smoothing, other return manipulation or suboptimal investment decisions.

If we only focus on investment funds that have extreme values compared to other members of the group, we should consider investment funds with a Bias Ratio of more than 1.38, which are the following 6 funds:

Bias Ratio:

1. Aegon ÓzonMaxx: 2,4
2. Aegon MoneyMaxx: 1,59
3. Erste DPM 1,54
4. Raiffeisen Hozam Prémium: 1,56
5. Aegon Smart Money: 1,42
6. Citadella Származtatott: 1,38

It is important to note, however, that whatever critical value we choose, we cannot say with certainty based on the Bias Ratio that investment funds above thr critical value will certainly use return manipulation or will be biased due to their suboptimal investment decisions, but it is clear that their distribution adjusted with the risk-free rate around zero in the one-one standard deviation wide interval shows disproportionality, which strongly suggests this.

### Comparison of Doubt Ratio and Bias Ratio, discontinuity-analysis

We are looking for the answer to the question of the relationship between the values of the Bias Ratio and the values of the Doubt Ratio and to what extent the two methods overlap. In addition, using discontinuity analysis, we perform a more detailed assessment of the rate distribution of suspect pre-rated investment funds (similarly to the Bias Ratio, analyzing returns corrected with RMAX index returns) to identify the presence of bias due to return manipulation or suboptimal investment decisions with greater certainty. According to the results, despite international experience, the Doubt Ratio proved to be a less reliable predictor than the Bias Ratio. By plotting the investment funds by the Bias Ratio and the Doubt Ratio, the relationship can be seen between the outliers (see Figure 7).

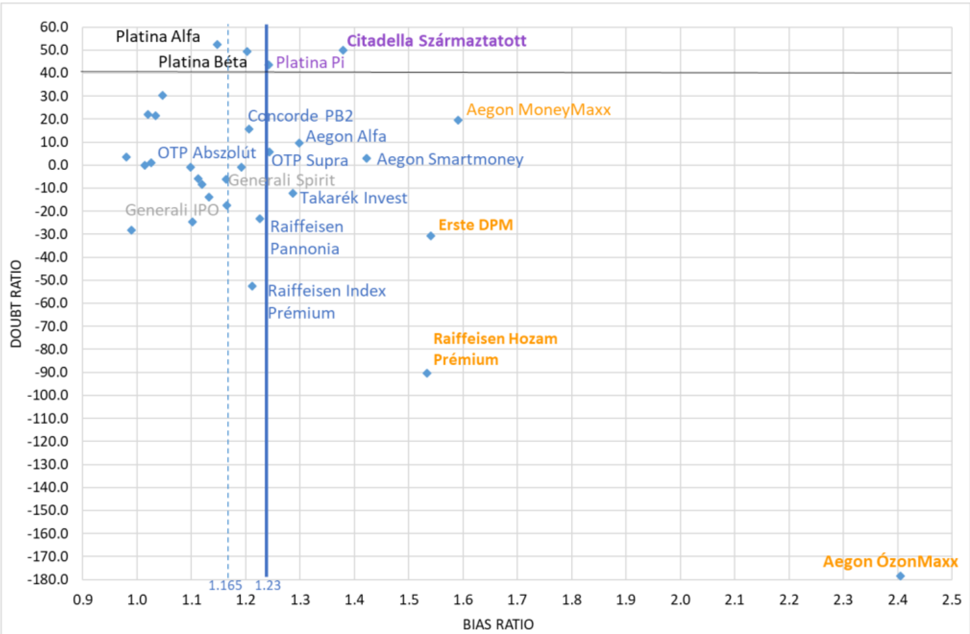


**Figure 7: Comparison of the Bias Ratio and the Doubt Ratio.**

However, in case of the Doubt Ratio, the values were below the critical level of about 150 defined by Brown et al. (2010) thus, the indicator did not clearly establish the existence of bias in any investment fund due to return manipulation or suboptimal investment decisions, there were 4 investment funds that had outstanding values also taking into account the Sharpe-ratio, compared to the other observed investment funds (see Figure 5). Of these, Platinum Pí and Citadella Származtatott have higher Bias Ratios than the median, so they can be considered as funds suggested for further analysis by two methods in terms of return manipulation or suboptimal investment decisions (see Figure 7 with purple caption). At the same time, the former investment fund is not yet spectacularly different from other investment funds based on the Bias Ratio. As described in Figure 5, and based on Figure 7, we assess that the Platinum Alfa and Platinum Beta investment funds are only distinguished by Doubt Ratio values that are fundamentally different from other investment funds (see Figure 7, with black captions), but not by Bias Ratio values. Although, based on the average rule of Abdulali (2006) (see Figure 7, the value of 1.165, represented by a dashed line), it is appropriate to subject the Platinum Beta fund to a more detailed analysis based on the Bias Ratio as well.

Aegon ÓzonMaxx, Aegon MoneyMaxx, Erste DPM, and Raiffeisen Hozam Premium are labeled in orange (Figure 7), as their Bias Ratios of more than 1.53, that are significantly higher than of the group, distinguishes them from other investment funds by suspecting potential return manipulation or bias due to suboptimal investment decisions, but they have no outstanding values, according to the Doubt Ratio.

According to Abdulali (2006), investment funds whose Bias Ratio values are above the median of the observed group, which in our case represents a critical value of 1.23, and 10 investment funds are worthy of further examination (while if 1.165, the average of the Bias Ratio is selected as the critical value, then 15 funds). We look at the distribution of returns adjusted with the risk-free rate of investment funds (with the return of RMAX index) around 0, searching for signs of discontinuity, which may also indicate potential return smoothing. Theoretically, if return smoothing or the creative valuation of individual illiquid asset is in the backgrond, then columns / classes showing the frequency of positive and negative returns directly at zero, may show a disproportion towards positive returns.

Accordingly, in the discontinuity analysis the following formula is used to construct the histograms following Bollen and Pool (2009), Silverman (1986):

$$h = 0{,}9 \min \left[\sigma ; \frac{Q3 - Q1}{1{,}34}\right] N^{-0{,}2} \quad , \qquad (18)$$

where h is the class width, $\sigma$ is the standard deviation of returns, N is the number of observed returns, Q3 and Q1 are the appropriate quartiles. According to Bollen and Pool (2009) when determining both h and plotting the histograms, we ignore the round 0 returns as they do not represent return smoothing but missing data or lack of trading.

To analyze the disproportions in the frequencies of positive and negative returns at 0, during our statistical test of the course of distribution on the histograms, to measure the frequency fit of each class interval to the normal distribution we used the following formula according to Bollen and Pool (2009) and Burgstahler and Dichev (1997):

$$Z = \frac{f - Np}{\sqrt{Np(1-p)}} \quad , \quad (19)$$

where f is the observed frequency in the given range interval, N number of observations, p the expected value of a given class width, which is the probability calculated from the distribution function of the normal distribution with the appropriate moments.

We begin our analysis with the two investment funds that both the Doubt Ratio and the Bias Ratio found to be highly suspicious in terms of the potential existence of return manipulation or suboptimal investment decisions, these are the Citadella Származtatott and Platina Pi investment funds. Following the analysis of Bollen and Pool (2009), we created the histograms with both class widhts according to Silverman (1986) in and its doubles, showing the class widths directly neighbouring 0 in black on Figure 8.

The histogram confirms the existence of a discontinuity aroud 0 in case of Citadella Számaztatott Fund (see Figure 8) and also confirmes a possible return manipulation or bias due to suboptimal investment decisions, since both normal class width and double class width have significant positive returns superiority at 0 as well in 185-241 and 270-377 proportion. The test statistic relative to normal distribution: 12.81 for negative and 19.12 for positive returns directly at 0 calculated with the class width of Silverman (1986), which, at all normal significance levels, show that for both class widhts, the observed frequencies do not follow the normal distribution but significantly exceed it (critical values are 1.96 and 2.58). At the same time, positive returns at 0 exceed normal distributions much more than negative returns at 0, the test statistics is about 1,5-times higher than of statistics experienced in case of negative returns directly at 0. Calculated with a 2x interval spacing, the experienced test statistic values are 10.3-18.8, i.e. the difference is approximately 1.8-times. Calculated with double class widths, the experienced test statistic values are 10.3-18.8, i.e. the difference is approximately 1.8-times.

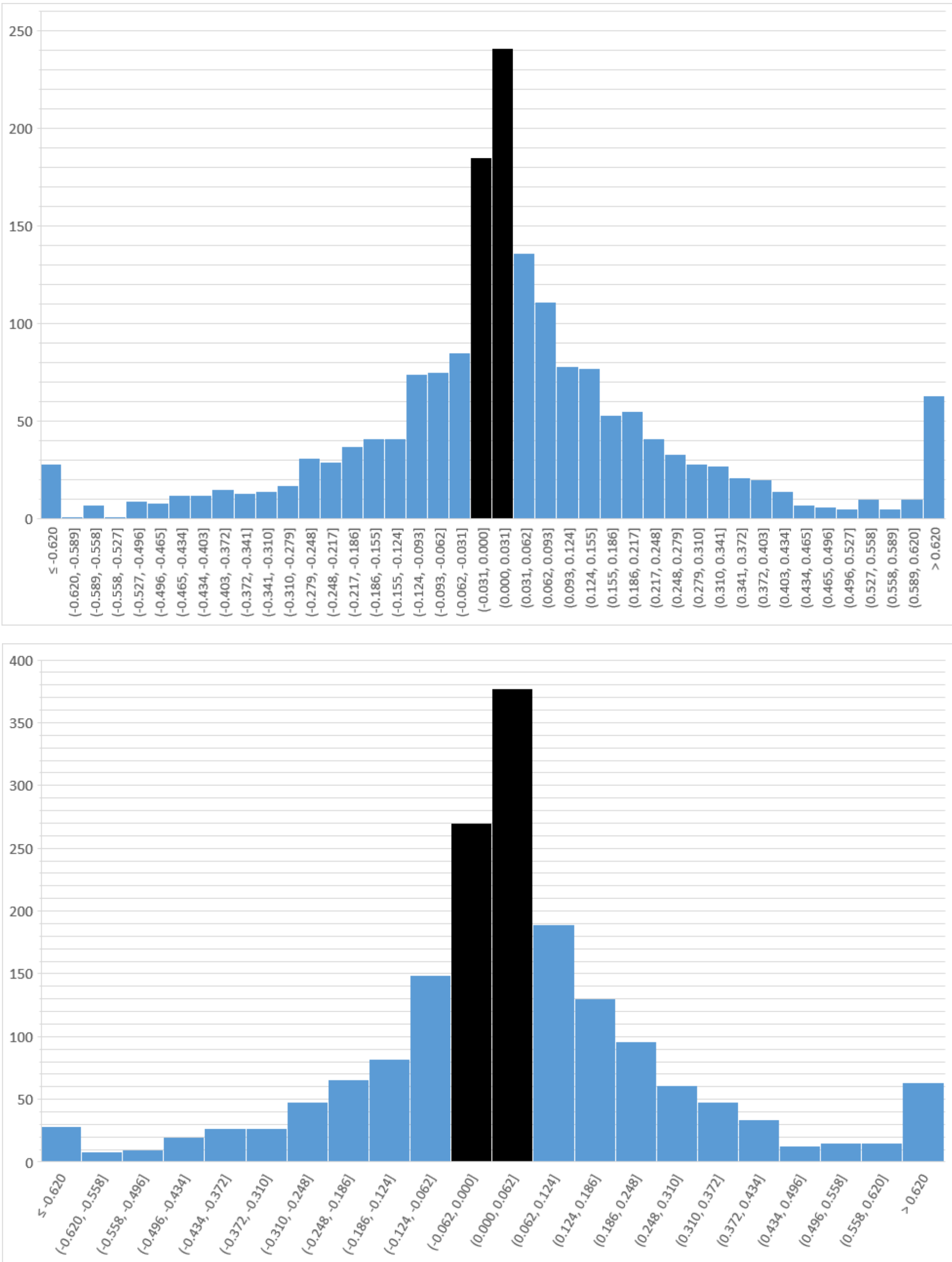


**Figure 8: Discontinuity analysis of Citadella Származtatott fund returns around 0.**

Bollen and Pool (2009), Brown et al. (2010), as well as Burgstahler and Dichev (1997) both found that negative returns near 0 showed a significant negative deviation relative to their expected value, while positive returns were statistically higher than their expected value supporting the hypothesis that frequency of positive returns next to 0 is probably increased by manipulation against negative returns next to 0. In contrast, in case of the former investment fund there was no difference in the direction of the observed differences of the two class widths, however, there was a significant difference in size in favour of positive returns. The difference in the magnitude of the differences can be used as a numerical indication to confirm the existence of discontinuity by observing the course of the histogram at the same time.

When reviewing the histograms of further 13 investment funds, we focused on cases where the frequency of positive returns near zero was significantly higher compared to its expected value than the frequency of negative returns near zero compared to its own expected value – since if that is not the case, then obviously, the investment fund manager cannot be blamed for artificially improving the ratio of positive returns around 0 to the detriment of negative returns near 0. In these cases, the ratio of the test statistic to a value of about 1.3 proved to be a dividing line, in case of higher values than that, the shape of the histogram also confirmed the existence of discontinuity, while for lower test statistic ratios the histogram showed no clear sign of discontinuity, return smoothing, or bias due to suboptimal investment decisions.

In case of the Aegon Ózonmaxx Investment Fund too, we found traces of bias due to potential return manipulation or suboptimal investment decisions (see Figure 9), since here the class widths directly around 0 are 160-201 and 236-384, respectively. The test statistic values are 15.2-20.7 and 13.6-27.7, so test statistic ratios are 1.36 and 2.0.

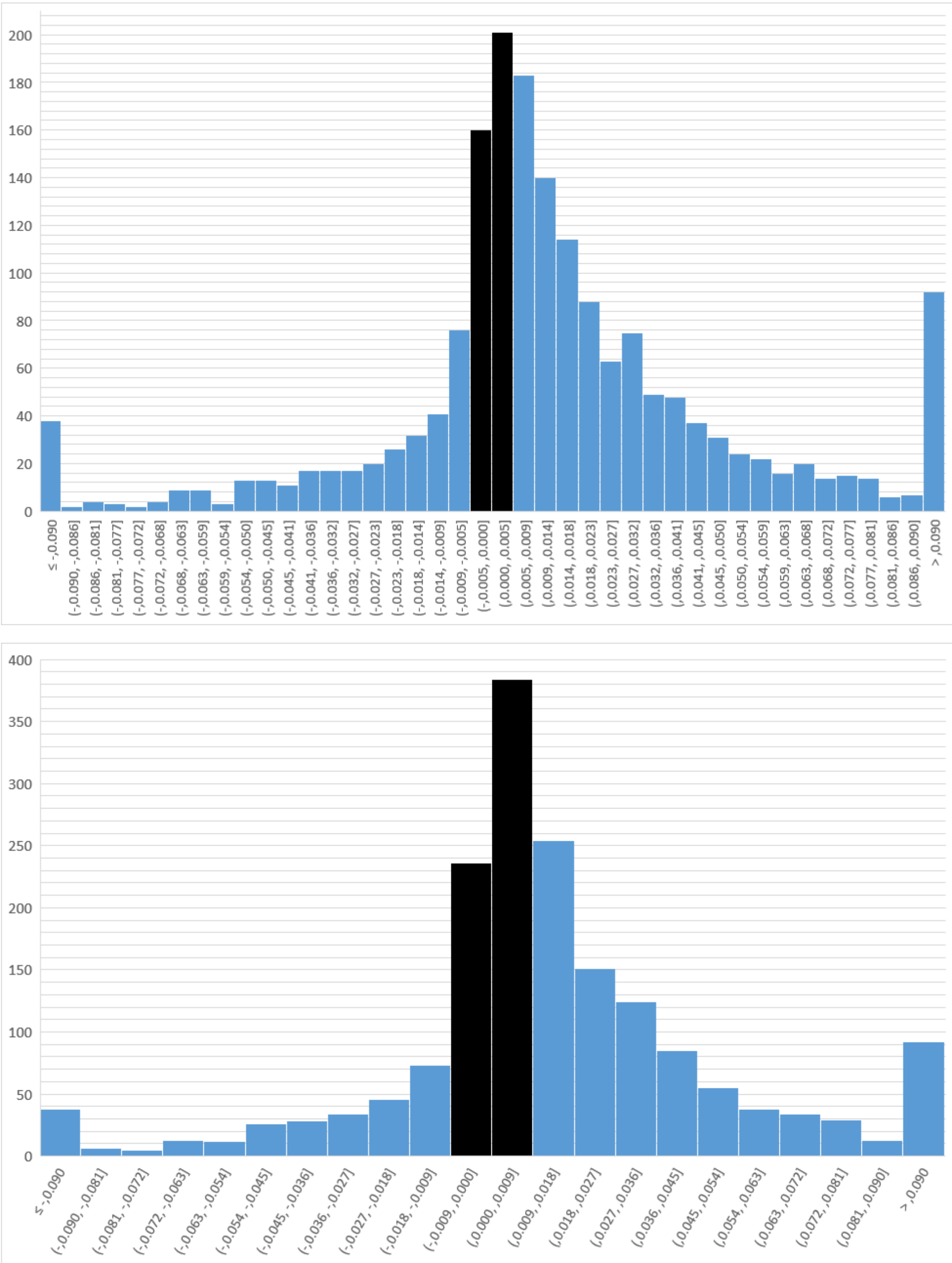


**Figure 9: Discontinuity analysis of the returns around 0 in case of Aegon Ózonmaxx fund.**

We performed the above discontinuity rate analysis using histograms with the appropriate class widths for further funds are filtered above by the Bias Ratio and the Doubt Ratio, and that can be suspected of return manipulation the best based on Figure 7 (4 according to the Bias Ratio, and 6 according to the Doubt Ratio). According to the Doubt Ratio, there is no sign of discontinuity for further funds returning high values, for

Platinum Pi, Platinum Beta and Platinum Alpha funds, which, however, confirms that earlier finding, that probably there is no return manipulation or bias due to suboptimal investment decisions because their value is well below the value of around 150, determined by Brown et al. (2006). Although according to the average rule of Abdulali (2006) for Bias Ratio values, it is worthwhile to look for traces of bias due to return manipulation or suboptimal investment decisions.

The Platina Alfa investment fund has the highest Doubt Ratio of 52.4, but the Bias Ratio is 1.15. The discontinuity analysis of returns around 0 clearly excludes the possibility of bias due to possible return manipulation or suboptimal investment decisions, since the frequency of positive returns is exceeding less the frequency appropriate to normal distribution than the frequency of negative returns (see figure 10): positive returns near 0 fall short 188-158 and 290-274, respectively, and test statistic values are 9.3-5.9 and 7.4-5.3, resulting in 0.64 and 0.71 test statistic ratios, respectively.

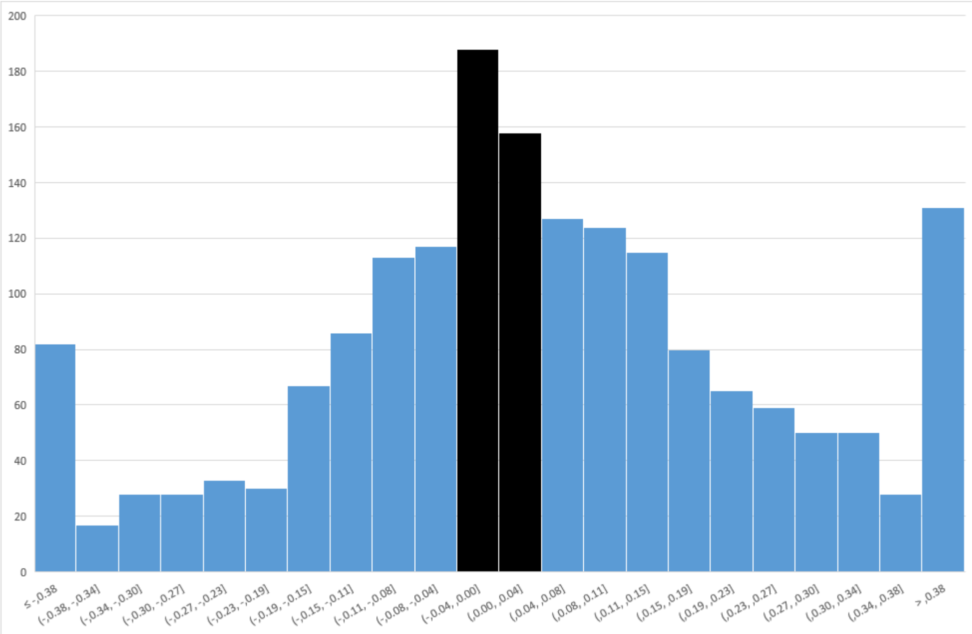
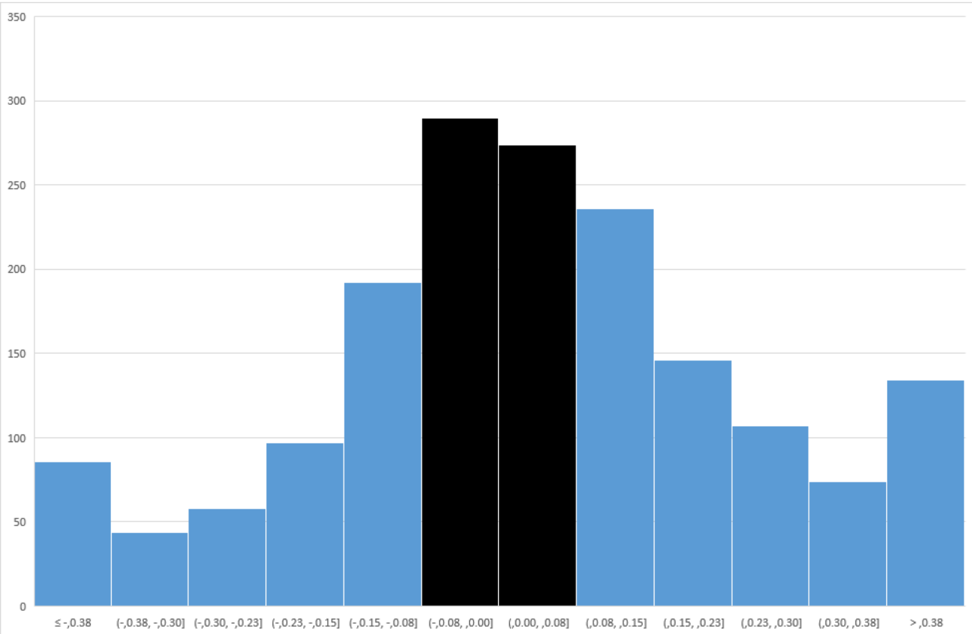


**Figure 10: Discontinuity analysis of the returns around 0 in case of Platina Alfa.**

In case of the other investment funds being the most suspected of bias by the Bias Ratio due to return manipulation or suboptimal investment decisions are the Raiffeisen Hozam Prémium, Erste DPM, Aegon MoneyMaxx funds, but only the former two show signs of discontinuity around 0. For Erste DPM, we observe the largest disproportion (see figure 11), in case of our observed investment funds in returns adjusted with risk-free rates around 0 with a 143-286 distribution, furthermore test statistic values are 13.6-34.2 and 12.7-33.9; which results in test statistic ratios of 2.5 and 2.7 respectively, here the existence of discontinuity is the most obvious among the observed investment funds.

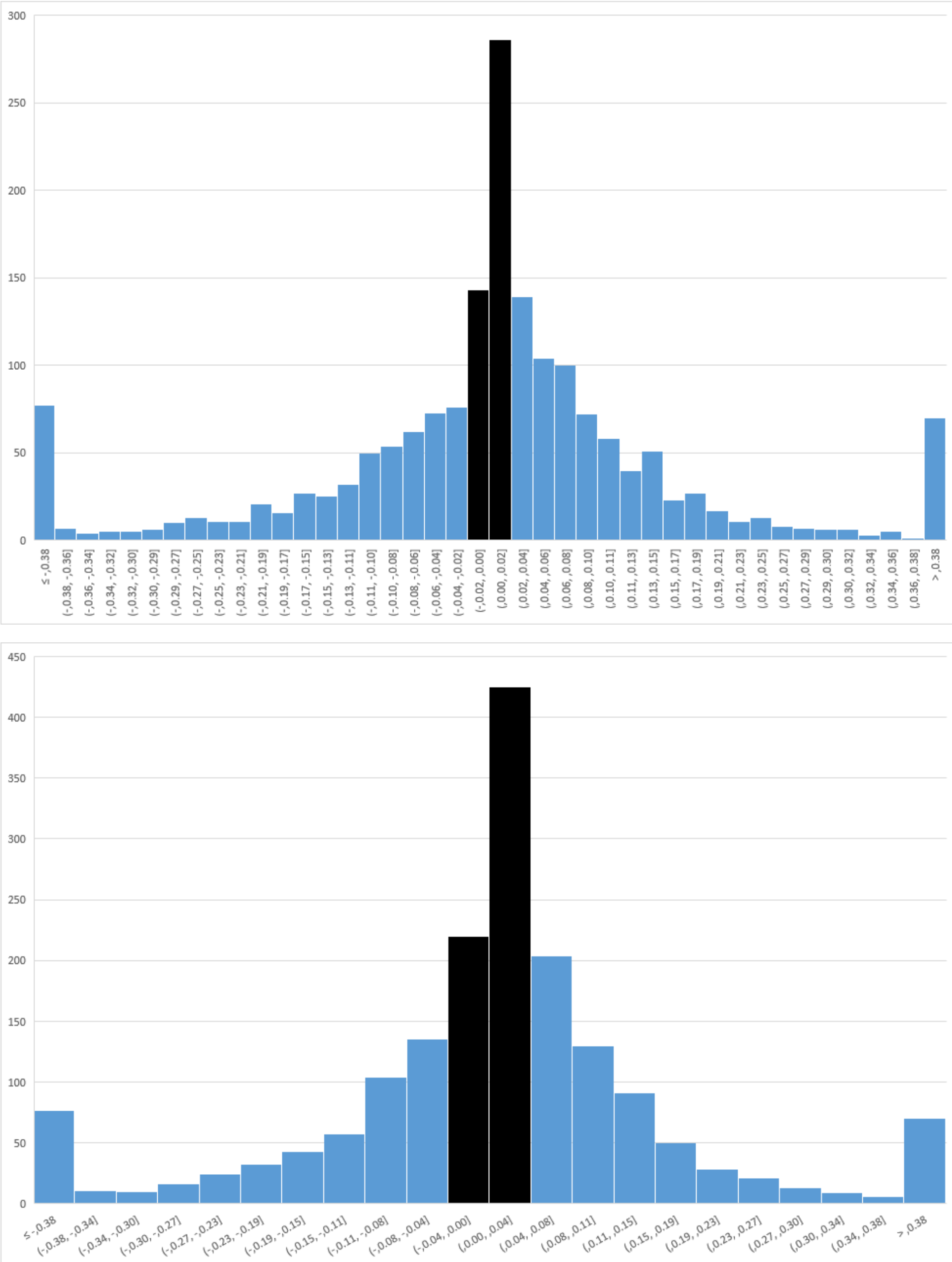


**Figure 11: Discontinuity analysis of the returns around 0 in case of Erste DPM fund.**

The Raiffeisen Hozam Prémium, with returns of 153-181 and 257-346, as well as test statistics of 1.4 and 2, also exhibits signs of discontinuity in its risk-adjusted returns. At the same time, in case of Aegon Money Maxx, the possibility discontinuity, thus the existence of bias due to return manipulation or suboptimal investment decisions can be excluded.

In case of the 8 further investment funds above the Bias Ratio average, we found no evidence of a discontinuity around 0, either bias due to return manipulation or suboptimal investment decisions.

In addition, we also examined Generali IPO and Generali Spirits too, whose Bias Ratios are just slightly below the average (1.1645), and they show no signs of discontinuity in their returns around 0. Similarly, the Concorde Columbus Fund showed no discontinuity either, which would be the next by its value based on the Doubt Ratio (30.4), if we extended our analysis –while its Bias Ratio is 1.05.

## Analysis of the investment policy of investment funds suspicious of return manipulation

The investment policy of the Concorde Citadella is based on global macroeconomic and fundamental analysis, including the use of technical analysis tools. Getting rid of loss-generating positions as quickly as possible (with stop-loss orders), preserving and increasing profitable positions are important principles[7]. Based on an interview with the fund manager, the fund invests in risk-free bonds in the absence of promising investment opportunities, and then, in case of promising trends, opens one or two large trend or spread positions combined with relatively narrow stop-loss orders. Thus, if the position goes bad and knocks out the stop-loss order, it will close the position with a small loss and then re-allocate the fund's assets in risk-free investment waiting for the next favourable opportunity. And if the market moves in the right direction and the fund manager achieves a return considered high enough by him, he can close the position. [8].

The possibility of sub-optimal investment decision arises in connection with the above strategy if the fund manager intends to "protect" the profit (and his bonus linked to it) achieved during the year by allocating in risk-free rate for the remainder of the year and does not seek a sufficiently diversified portfolio for this period, since compared to risk-free rate it is more than likely that there would also have been investments for the remainder of the year, that could have produced value-added, positive-risk-adjusted

[7] https://premiumbanking.con.hu/befektetesi-alapok/abszolut-hozamu-alapok/

[8] Based on an interview with investment manager Dániel Móricz from Concorde / Hold Fund Management.

returns. Thus, in case of the Concorde Citadella, it appears appropriate to classify the demonstrated return manipulation into the category of dynamic manipulation, and the investment policy as described above, refers to suboptimal decisions during periods of risk-free refuge/allocation, not to conscious manipulation. It is an interesting question whether our manipulation detection methods would signal bias doe to suboptimal investment decisions even if the fund manager changed its strategy, and in the future allocated his assets into some liquid, diversified but not completely risk-free rate.

Aegon Ózonmaxx invests the vast majority of its assets based on the investment policy in bonds issued or guaranteed by the Hungarian state or states with a credit rating at least equal to or better than to its current credit rating, quasi-sovereign companies, national banks or supranational institutions while invest a small proportion of the fund's assets in risky assets - domestic and foreign equities, stock indices, higher-risk bonds, foreign exchanges, commodity products, and collective investment securities[9]. According to an interview with the fund manager, the fund served as a capital guaranteed fund during the period under review, meaning that it held essentially risk-free bonds and risked only the annual returns in risky positions, that seemed profitable, and in this way collected the excess return over risk-free rate by "basis-points".[10] In this case, it does not seem justified that there are two methods suspecting it of return manipulation, as its investment strategy explains the suspicious return distribution.

According to its investment policy, Aegon Moneymaxx fund focuses on investing in the area that promises the highest possible rate at any given moment: including assets in both Hungarian and international money and capital market, and within these, the fund manager can move with dynamic portfolio allocation to maximize returns. In theory, the ratio of risky assets in the fund may range from 0% to 100%, but in recent years this proportion has not increased above 30-40%[11]. However, according to an interview with the fund manager, the Aegon Monyemaxx fund, in contrast to the Concorde Citadella fund, which takes on one or two large positions, opens many small risky positions, which

[9] https://www.aegonalapkezelo.hu/jelentesek-kozlemenyek/alapok-dokumentumai/kiemelt-befektetoi-informaciok/

[10] Based on an interview András Lancsák fund manager from Aegon Fund Management.

[11] https://www.aegonalapkezelo.hu/jelentesek-kozlemenyek/alapok-dokumentumai/kiemelt-befektetoi-informaciok/

it manages separately [12]. However, according to an interview with the fund manager, the Aegon Monyemaxx fund, in contrast to the Concorde Citadella fund, which takes on one or two large positions, opens many small risk positions, which it manages separately. As a result, its investment policy is much more diversified and full risk aversion can only occur towards the end of the year. It is understandable that despite the dynamic allocations between risk-free and risky positions (which it resembles the Concorde Citadella fund by positions), why only the Bias Ratio found it suspicious, but the discontinuity analysis no longer.

According to Erste DPM's investment policy, the fund aims to provide investors with returns that are competitive with global equity markets. The fund acts as a fund of funds, i.e. freely allocates its capital among different equity funds (besides global funds, fund that cover regional funds, industry sectors and investment styles - value, growth - equity funds). According to the current state of capital markets, applying an active investment policy. Based on Erste DPM's investment policy, dynamic allocation is primarily made among investment funds covering different stock markets, so that the fund manager cannot be accused of missing out on potential investment opportunities because he does not flee in risk-free investments. In case of Erste DPM, therefore, in knowledge of the investment policy, it does not appear to be justified that it was accused of return manipulation by two methods.

The composition of Raiffeisen Hozam Prémium fund's portfolio is primarily determined by the outlook for the currency and interest rate markets. The fund invests its assets in derivatives, in addition to government securities, other debt securities and deposits, and to a limited extent in other risky assets (equities, certificates, etc.). The fund is currently pursuing a strategy to limit the fund's greatest possible loss over one year based on the value at risk method below 11.63% with high probability starting from July 3, 2017[13]. Based on an interview with the fund manager, the Raiffeisen Hozam Prémium is a bond-overweighed fund, which holds bonds that are slightly riskier than risk-free and therefore they try to collect return premiums for a small amount of additional risk, relative to risk-free rate. In its case, the suspicion of return manipulation detected by

[12] Based on an interview András Lancsák fund manager from Aegon Fund Management.
[13] https://alapok.raiffeisen.hu/alapok/hozam-premium

even two methods, is caused by the fact that we see a really steady overperformance in the distribution of the returns compared to the risk-free rate. Thus, it does not seem justified, that even two methods suspect the fund of return manipulation as their investment strategy explains the suspicious return distribution and in case of bond-overweighed funds statistical methods that investigate the return distribution are less reliable.

The Aegon Smartmoney fund uses a variety of analytical techniques to select asset classes, investment funds that have the highest potential for appreciation and invest through the purchase of units and collective investment securities[14]. Similar to Erste DPM's investment policy, dynamic allocation is primarily carried out among investment funds (primarily absolute return funds) covering different equity markets[15]. Thus, in this case, it is not possible to accuse the fund manager of missing out on potential investment opportunities, as he almost never allocates all his assets to risk-free investments for escape/return protection. Unlike the Erste DPM fund, Aegon Smartmoney's discontinuity analysis does not confirm the existence of return manipulation either.

The Platina Pí is based on fundamental analysis, but also takes into account technical timing, during a so-called bottom-up analysis in case of attractive investments examines the medium-term macroeconomic environment (top-down method). If the results of the two approaches point in the same direction, the selected position will be executed in 2-3 steps. If, on the other hand, the fund manager does not see sufficient opportunity in higher-risk instruments, he invests the fund's capital in low-risk assets until good buying or selling opportunities are available[16]. Based on the investment policy, the Platina Pí fund applies a similar dynamic allocation strategy to risk-free and risky assets like Concorde Citadella[17], however, like Aegon Moneymaxx, this fund also takes smaller and thus more diversified positions than the Concorde Citadella, and like for Aegon Moneymaxx, discontinuity analysis did not confirm the existence of return manipulation for this fund either.

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[14] https://www.aegonalapkezelo.hu/wp-content/uploads/2019/06/sm-a-2019.pdf

[15] Based on an interview András Lancsák fund manager from Aegon Fund Management.

[16] https://www.erstemarket.hu/befektetesi_alapok/alap/HU0000709969

[17] Based on an interview with investment manager Dániel Móricz from Concorde / Hold Fund Management.

## Summary of traces of return manipulation and different signalling methods

Summarizing, on the sample of 31 investment funds analysed, the Doubt Ratio indicated suspicion of return smoothing for 4 funds by the deviation from group average, out of which discontinuity analysis showed the likely presence of return manipulation once, that based on investment policies and on interviews with investment fund managers may also be classified as a possibly periodically suboptimal investment strategy in case of the Concorde Citadella fund.

In case of the Bias Ratio, out of 10 funds above the median got confirmation based on the discontinuity analysis 4 times. Of these 4 funds, Aegon Ózonmaxx is a capital protected bond-overweighed fund, while Raiffeisen Hozam Prémium is a bond overweighed fund, so in their case the Bias Ratio and the discontinuity analysis are less reliable and based on their investment policy neither the suspicion on return manipulation nor on suboptimal decision seem to be well based. Erste DPM works as a fund of funds, so any type of manipulation is unlikely knowing the investment policy. In case of the Concorde Citadella fund, the investment policy seems justified in assuming the existence of investment strategies that are considered suboptimal at periodic intervals.

Overall, the Bias Ratio seems to be a more reliable indicator of return smoothing than the Doubt Ratio as its results are confirmed by several methods. However, it should be taken into consideration, that the Doubt Ratio could have only be used on the sample to identify investment funds with strikingly different values compared to the group, since no investment fund reached the critical value of 150.

It is worth noting that, in the knowledge of the investment policies, multiple parallel suspicious signals by multiple methods could be considered well-founded only in case of one single fund, while in other cases their reliability could be questioned. Only in case of the Concorde Citadella fund were consistent signals found through the Doubt Ratio, Bias Ratio and discontinuity analysis, as well as by the analysis of the investment policy.

Another important factor is that the analysis was carried out on a relatively small sample, so it cannot be considered as generally proven that this difference would appear on larger samples in the same proportion between the two indicators. Also, it is worth noting that the Doubt Ratio measures implied risk aversion and establishes a link between returns and the taken risk through MPPM, while the Bias Ratio only analyses the distribution of returns.

### 2.2.4. Comparison of the Ingersoll et al. (2007) and Brown et al. (2010) MPPM values and ranking

In this chapter we compare Ingersoll et al. (2007) and Brown et al. (2010) MPPM values and rankings. With Ingersoll et al. (2007) and Brown et al. (2010) formula we obtain very similar results for MPPM in terms of both index value and rank. This means that the correlation is 1 for MPPM values at risk rejection coefficient 2, and around 0.9999 for parameters 3 and 4. The rank-correlation also has a value of 1 with a risk aversion factor of 2 and 4 showing a full match, while with a coefficient of 3, the rank-correlation is 0.9996, indicating almost complete match, this means that 30 of the 31 examined funds will be given the same ranking and there are only two funds that switch ranking based on the two methods. Thus, in the ranking of the MPPM of 31 funds with 3 risk aversion factors, out of the 93 cases we found only 2 differences, i.e. there is a 97.85% match between the two methods.

Percentage deviations of MPPM values are generally less than 1% according to the two calculation methods (see Table 18). In case of the OTP EMDA fund a 2.34% deviation can be seen with a risk aversion factor of 4, which is one of the largest % deviations, but it does not cause any change in the ranking order. On the one hand, this is because we see MPPM values very close to 0 (Ingersoll et al. (2007) -0,0105, Brown et al. (2010) -0,0108), so there is a relatively small change in the absolute value (+0.0002) and represents a large percentage change between the two calculation methods. Another explanation why there is no order change is that compared to this otherwise relatively small change in absolute value, the MPPM value of the subsequent investment fund is at a sufficient distance.

OTP Supra Fund hangs out the line and changes position with Concorde Columbus fund at risk aversion factor 3 changing from Ingersoll et al. (2007) formula to Brown et al. (2010) formula. While the values of Concorde Columbus for the two methods are equal to 6 decimals for each risk aversion factor, in case of OTP Supra with a risk aversion factor of 3 we saw a 3.4% increase in MPPM value according to the Brown et al.-

method, which is also the largest difference in absolute value (0.0013) with a risk aversion factor of 4, with 0.003 and 13.4% higher than the Brown et.al (2010) result. The explanation of the value change in MPPM that affects the order of the OTP Supra fund is that while this fund has the second highest return and its standard deviation of returns is the fourth highest, so based on the results, the MPPM's linear approximation with Brown et al. (2010) less punishes risk relative to the calculation of Ingersoll et al. (2007). The order change between the two funds can also be explained by the fact that with a risk aversion factor of 3, the two methods differ relatively high in absolute values and relative to this, the difference between the MPPM values of the two funds is relatively small.

Summarizing, with a risk aversion factor of 2 and 4 the ranking matches for both two methods for all 31 funds. We find a difference only with a risk aversion factor of 3, when out of 31 funds 29 gets the same ranking, and there are only two funds witch exchange places calculated with the two methods. This is caused on hand by the fact, that with a risk aversion factor of 3 the difference between the MPPM values of the two funds is relatively small. On the other hand, one of the funds in question has a return which is the second highest and its return volatility is the fourth biggest, while both values of the other fund can be considered as of average and the results prove that the Brown et al. (2010) linear approximation of MPPM punishes risk less than the Ingersoll et al. (2007) calculation method.

| | Aberd I | Aegon A | Aegon S | Citadella | Aegon M | Aegon Ó | Budapest K | OTP Új E | Conc Col | Conc PB2 | Conc Rub | Conc VM | Erste Mu | Erste D |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Ingersoll** | | | | | | | | | | | | | | |
| MBTM(2) | -0.0098 | 0.0143 | 0.0004 | 0.0477 | 0.0084 | -0.0076 | -0.0264 | -0.0201 | 0.0398 | 0.0051 | 0.0549 | -0.0006 | -0.0421 | -0.0294 |
| MBTM(3) | -0.0131 | 0.0124 | 0.0000 | 0.0467 | 0.0079 | -0.0076 | -0.0297 | -0.0220 | 0.0384 | 0.0047 | 0.0522 | -0.0012 | -0.0437 | -0.0303 |
| MBTM(4) | -0.0164 | 0.0105 | -0.0004 | 0.0457 | 0.0074 | -0.0077 | -0.0331 | -0.0239 | 0.0370 | 0.0043 | 0.0495 | -0.0018 | -0.0453 | -0.0312 |
| MBTM(2) rank | 18 | 10 | 13 | 3 | 11 | 16 | 22 | 20 | 6 | 12 | 1 | 14 | 27 | 25 |
| MBTM(3) rank | 18 | 9 | 13 | 2 | 11 | 15 | 23 | 20 | 5 | 12 | 1 | 14 | 27 | 24 |
| MBTM(4) rank | 19 | 9 | 12 | 2 | 10 | 14 | 24 | 20 | 5 | 11 | 1 | 13 | 26 | 23 |
| **Brown** | | | | | | | | | | | | | | |
| MBTM(2) | -0.0098 | 0.0143 | 0.0004 | 0.0477 | 0.0084 | -0.0076 | -0.0264 | -0.0201 | 0.0398 | 0.0051 | 0.0549 | -0.0006 | -0.0421 | -0.0294 |
| MBTM(3) | -0.0131 | 0.0124 | 0.0000 | 0.0467 | 0.0079 | -0.0076 | -0.0297 | -0.0220 | 0.0384 | 0.0047 | 0.0522 | -0.0012 | -0.0437 | -0.0303 |
| MBTM(4) | -0.0164 | 0.0105 | -0.0004 | 0.0457 | 0.0074 | -0.0077 | -0.0331 | -0.0239 | 0.0370 | 0.0043 | 0.0494 | -0.0018 | -0.0453 | -0.0312 |
| MBTM(2) rank | 18 | 10 | 13 | 3 | 11 | 16 | 22 | 20 | 6 | 12 | 1 | 14 | 27 | 25 |
| MBTM(3) rank | 18 | 9 | 13 | 2 | 11 | 15 | 23 | 20 | 6 | 12 | 1 | 14 | 27 | 24 |
| MBTM(4) rank | 19 | 9 | 12 | 2 | 10 | 14 | 24 | 20 | 5 | 11 | 1 | 13 | 26 | 23 |
| **Ingersoll-Brown Δ** | | | | | | | | | | | | | | |
| MBTM(2) | 2.5E-06 | -1E-06 | 2.8E-07 | 8.58E-07 | 1.2E-07 | 4.3E-08 | 2.215E-06 | -2E-06 | 8.02E-07 | 2.12E-07 | 1.32E-06 | 3.73E-07 | 2.4E-07 | 3E-07 |
| MBTM(3) | 6.3E-06 | -7E-06 | 7.1E-07 | 2.29E-06 | -4.6E-08 | 1.2E-07 | 4.546E-06 | -9E-06 | 1.62E-06 | 4.26E-07 | 2.16E-06 | 8.19E-07 | -9E-07 | 3E-07 |
| MBTM(4) | 1.1E-05 | -2E-05 | 1.3E-06 | 4.27E-06 | -5.2E-07 | 2.4E-07 | 6.238E-06 | -2E-05 | 2.44E-06 | 6.4E-07 | 2.49E-06 | 1.33E-06 | -3.5E-06 | -2E-07 |
| MBTM(2) rank | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| MBTM(3) rank | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | -1 | 0 | 0 | 0 | 0 | 0 |
| MBTM(4) rank | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **Ingersoll-Brown Δ%** | | | | | | | | | | | | | | |
| MBTM(2) | -0.0259 | -0.0086 | 0.0792 | 0.0018 | 0.0015 | -0.0006 | -0.0084 | 0.0081 | 0.0020 | 0.0042 | 0.0024 | -0.0624 | -0.0006 | -0.0011 |
| MBTM(3) | -0.0484 | -0.0579 | -4.5688 | 0.0049 | -0.0006 | -0.0016 | -0.0153 | 0.0397 | 0.0042 | 0.0090 | 0.0041 | -0.0688 | 0.0020 | -0.0009 |
| MBTM(4) | -0.0681 | -0.1728 | -0.3230 | 0.0093 | -0.0070 | -0.0032 | -0.0188 | 0.0900 | 0.0066 | 0.0147 | 0.0050 | -0.0747 | 0.0078 | 0.0008 |

| | Sovereign P | Generali Sp | Generali Ti | Generali IP | OTP Abs | OTP EMDA | OTP G10 | OTP Supra | Platina Al | Platina Be | Platina De | Platina Ga | Platina Pí A | Raiff Hoz | Raiff Ind | Raiff Pan | Takarék In |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Ingersoll** | | | | | | | | | | | | | | | | | |
| MBTM(2) | -0.0625 | -0.0481 | -0.0394 | -0.0236 | -0.0073 | 0.0333 | -0.0477 | 0.0510 | 0.0441 | 0.0182 | -0.0275 | 0.0356 | 0.0454 | -0.0141 | -0.0199 | -0.0268 | -0.0082 |
| MBTM(3) | -0.0646 | -0.0505 | -0.0418 | -0.0265 | -0.0099 | 0.0114 | -0.0719 | 0.0373 | 0.0432 | 0.0178 | -0.0412 | 0.0338 | 0.0443 | -0.0143 | -0.0203 | -0.0279 | -0.0088 |
| MBTM(4) | -0.0668 | -0.0530 | -0.0443 | -0.0295 | -0.0126 | -0.0105 | -0.0961 | 0.0228 | 0.0424 | 0.0174 | -0.0549 | 0.0320 | 0.0432 | -0.0144 | -0.0207 | -0.0289 | -0.0093 |
| MBTM(2) rank | 30 | 29 | 26 | 21 | 15 | 8 | 28 | 2 | 5 | 9 | 24 | 7 | 4 | 18 | 19 | 23 | 17 |
| MBTM(3) rank | 29 | 28 | 26 | 21 | 17 | 10 | 30 | 6 | 4 | 8 | 25 | 7 | 3 | 18 | 19 | 22 | 16 |
| MBTM(4) rank | 29 | 27 | 25 | 22 | 17 | 16 | 30 | 7 | 4 | 8 | 28 | 6 | 3 | 18 | 19 | 21 | 15 |
| **Brown** | | | | | | | | | | | | | | | | | |
| MBTM(2) | -0.0625 | -0.0481 | -0.0394 | -0.0236 | -0.0073 | 0.0333 | -0.0477 | 0.0513 | 0.0441 | 0.0182 | -0.0275 | 0.0356 | 0.0454 | -0.0141 | -0.0199 | -0.0268 | -0.0082 |
| MBTM(3) | -0.0644 | -0.0505 | -0.0418 | -0.0265 | -0.0099 | 0.0112 | -0.0719 | 0.0386 | 0.0432 | 0.0178 | -0.0410 | 0.0338 | 0.0443 | -0.0143 | -0.0203 | -0.0279 | -0.0088 |
| MBTM(4) | -0.0663 | -0.0530 | -0.0443 | -0.0294 | -0.0126 | -0.0108 | -0.0961 | 0.0259 | 0.0424 | 0.0174 | -0.0546 | 0.0320 | 0.0432 | -0.0144 | -0.0207 | -0.0289 | -0.0093 |
| MBTM(2) rank | 30 | 29 | 26 | 21 | 15 | 8 | 28 | 2 | 5 | 9 | 24 | 7 | 4 | 18 | 19 | 23 | 17 |
| MBTM(3) rank | 29 | 28 | 26 | 21 | 17 | 10 | 30 | 5 | 4 | 8 | 25 | 7 | 3 | 18 | 19 | 22 | 16 |
| MBTM(4) rank | 29 | 27 | 25 | 22 | 17 | 16 | 30 | 7 | 4 | 8 | 28 | 6 | 3 | 18 | 19 | 21 | 15 |
| **Ingersoll-Brown Δ** | | | | | | | | | | | | | | | | | |
| MBTM(2) | -5.023E-05 | -4.24E-06 | -5.592E-06 | -3.91E-06 | 1.2E-06 | 3.848E-05 | 2E-05 | -0.000292 | 2.23E-07 | 4.79E-07 | -2.3E-05 | 9.8E-07 | 3.68E-08 | 5.6E-08 | 1.12E-07 | -1.3E-06 | 6.043E-07 |
| MBTM(3) | -0.0002099 | -2.02E-05 | -2.557E-05 | -1.93E-05 | 1.7E-06 | 0.0001234 | 4.6E-05 | -0.001265 | -1.1E-07 | 1.48E-06 | -0.00011 | 1.83E-06 | -1.14E-06 | 5.18E-08 | 3.33E-08 | -6.4E-06 | 1.748E-06 |
| MBTM(4) | -0.0004901 | -4.88E-05 | -6.061E-05 | -4.67E-05 | 1.3E-06 | 0.0002462 | 6.7E-05 | -0.003063 | -1E-06 | 2.98E-06 | -0.00028 | 2.48E-06 | -3.62E-06 | -1.3E-08 | -2.4E-07 | -1.5E-05 | 3.402E-06 |
| MBTM(2) rank | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| MBTM(3) rank | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| MBTM(4) rank | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **Ingersoll-Brown Δ%** | | | | | | | | | | | | | | | | | |
| MBTM(2) | 0.0803 | 0.0088 | 0.0142 | 0.0166 | -0.0161 | 0.1156 | -0.0418 | -0.5718 | 0.0005 | 0.0026 | 0.0842 | 0.0028 | 0.0001 | -0.0004 | -0.0006 | 0.0048 | -0.0074 |
| MBTM(3) | 0.3250 | 0.0400 | 0.0611 | 0.0728 | -0.0167 | 1.0852 | -0.0637 | -3.3893 | -0.0003 | 0.0083 | 0.2733 | 0.0054 | -0.0026 | -0.0004 | -0.0002 | 0.0229 | -0.0200 |
| MBTM(4) | 0.7339 | 0.0921 | 0.1367 | 0.1586 | -0.0104 | -2.34 | -0.0700 | -13.4352 | -0.0024 | 0.0171 | 0.5013 | 0.0078 | -0.0084 | 0.0001 | 0.0012 | 0.0533 | -0.0364 |

**Table 18: Comparison of Ingersoll et al. (2007) - and Brown et al. (2010) MPPM values and rankings.**

With the approximation (16) used by Brown et al. (2010) the Doubt Ratio can be calculated as a ratio of the average excess return and the variance of the excess return calculated from the sample:

$$\text{Doubt Ratio} = \text{DR} \approx \frac{2\bar{x}}{(s_x^*)^2} + 1 \quad . \qquad (20)$$

Doubt Ratio can be defined by Brown et.al. (2010) (16) and also by comparing MPPM values calculated with different risk aversion factors too, estimating the implied risk aversion factor. If we use MPPM values (see (14)) defined by Ingersoll et al. (2007) the formula is as follows:

$$\text{Doubt Ratio} = \text{DR} = \frac{\widehat{\Theta}_{Ingersoll}(2)}{\widehat{\Theta}_{Ingersoll}(2) - \widehat{\Theta}_{Ingersoll}(3)} + 2 \quad . \qquad (21)$$

If Brown et al. (2010) defined MPPM (see (15)) values are used, the formula is modified as follows:

$$\text{Doubt Ratio} = \text{DR} = \frac{\widehat{\Theta}_{Brown}(2)}{\widehat{\Theta}_{Brown}(2) - \widehat{\Theta}_{Brown}(3)} + 2 \quad . \qquad (22)$$

Calculating with the MPPM-based formula of Brown et al. (2010) (22), and from the Brown et al. (2010) approximation (20) we obtain a substantially complete match for the values of the Doubt Ratio (up to thirteen decimal places), and accordingly, the calculated order is exactly the same, the rank-correlation and correlation values are 1. Ingersoll et al. (2007) - and Brown et al. (2010) -based MPPM (and Brown et al. (2010) approximation) return very similar values, with a correlation of 0.9999 and a rank-correlation of 0.9996. In case of 29 out of the 31 examined investment funds i.e. 93.5% of the funds, there is complete match in the ranking of the Doubt Ratio by calculating with all three methods.

In the Ingersoll et al. (2007) and Brown et al. (2010) based Doubt Ratio values (calculated using MPPM and Brown's approximation) significant differences are found for the following funds: Platina Delta, OTP G10, OTP Supra, and Sovereign PB derivative fund (see Table 19). Of these, the differences in value cause a change in ranking only in case of the latter. For the former, the relatively small change in absolute value is coupled with the fact that the subsequent Doubt Ratio is far enough to avoid order changes despite the relatively high percentage change (see, for example, the 0.0156 absolute changes for the Platina Delta and its associated 72.3% value). The Sovereign PB derivative fund, on the other hand, fall one place behind in the order of Brown et al. (2010) relative to Ingersoll et al. (2007) order so that the values of the preceding Erste DPM were hardly altered. That is, the change in order is ultimately caused by the significant depreciation (-8.87%) experienced at Sovereign PB derivative fund and that the fund that follows it has a reasonably close Doubt Ratio value relative to it to change the order. For this fund, Ingersoll et al. (2007) has the third highest absolute value change in MPPM and the fifth largest percentage change with a risk aversion factor of 4 relative to the Brown et al. (2010) version fund (0.7339%), and according to the experienced, the differences in MPPM was further inherited magnified into the values of the Doubt Ratio (8.87%).

Summarizing, calculating from the Ingersoll et al. (2007) and Brown et al. (2010) based MPPM we got very similar results for the Doubt Ratio. In case of 29 out of 31 of the investigated funds, i.e. 93.5% of the funds the ranking completely matches for all three calculation methods. The difference is caused by the material depreciation examined for one fund changing from Ingersoll et al. (2007) based method to Brown et al. (2010) based one, and that the Doubt Ratio of the following fund is relatively close, while its value did not change essentially. According to the experienced, the differences in MPPM was further inherited magnified into the values of the Doubt Ratio.

| | Aberd I | Aegon A | Aegon S | Citadella | Aegon M | Aegon Ó | Budapest K | OTP Új E | Conc Col | Conc PB2 | Conc Rub | Conc VM | Erste Mu | Erste D | Sovereign P |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **DR(Ingersoll)** | -1.005 | 9.653 | 2.959 | 49.855 | 19.683 | -178.505 | -5.800 | -8.440 | 30.443 | 15.670 | 22.153 | 0.993 | -24.754 | -30.668 | -28.238 |
| **DR(Brown)** | -1.002 | 9.678 | 2.957 | 49.785 | 19.689 | -178.160 | -5.795 | -8.478 | 30.426 | 15.662 | 22.147 | 0.993 | -24.773 | -30.671 | -30.743 |
| **DR(Brown approx.)** | -1.002 | 9.678 | 2.957 | 49.785 | 19.689 | -178.160 | -5.795 | -8.478 | 30.426 | 15.662 | 22.147 | 0.993 | -24.773 | -30.671 | -30.743 |
| **DR(Ingersoll)-DR(Brown) Δ** | -0.0027 | -0.0252 | 0.0018 | 0.0694 | -0.0061 | -0.3455 | -0.0047 | 0.0380 | 0.0172 | 0.0084 | 0.0067 | -0.0001 | 0.0195 | 0.0026 | 2.5043 |
| **DR(Ingersoll)-DR(Brown approx.) Δ** | -0.0027 | -0.0252 | 0.0018 | 0.0694 | -0.0061 | -0.3455 | -0.0047 | 0.0380 | 0.0172 | 0.0084 | 0.0067 | -0.0001 | 0.0195 | 0.0026 | 2.5043 |
| **DR (Brown)-DR(Brown approx.) Δ** | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| **DR(Ingersoll)-DR(Brown) Δ%** | 0.2689 | -0.2612 | 0.0622 | 0.1393 | -0.0309 | 0.1935 | 0.0814 | -0.4498 | 0.0566 | 0.0538 | 0.0304 | -0.0130 | -0.0787 | -0.0086 | -8.8685 |
| **DR(Ingersoll)-DR(Brown approx.)Δ%** | 0.2689 | -0.2612 | 0.0622 | 0.1393 | -0.0309 | 0.1935 | 0.0814 | -0.4498 | 0.0566 | 0.0538 | 0.0304 | -0.0130 | -0.0787 | -0.0086 | -8.8685 |
| **DR(Brown)-DR(Brown approx.) Δ%** | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| **DR(Ingersoll) rank** | 18 | 10 | 13 | 2 | 8 | 30 | 18 | 20 | 5 | 9 | 6 | 14 | 25 | 27 | 26 |
| **DR(Brown) rank** | 18 | 10 | 13 | 2 | 8 | 30 | 18 | 20 | 5 | 9 | 6 | 14 | 25 | 26 | 27 |
| **DR(Brown approx.)rank** | 18 | 10 | 13 | 2 | 8 | 30 | 18 | 20 | 5 | 9 | 6 | 14 | 25 | 26 | 27 |
| **DR(Ingersoll)-DR(Brown)rankΔ** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | -1 |
| **DR(Ingersoll)-DR(Brown app.)rankΔ** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | -1 |
| **DR(Brown)-DR(Brown app.)rankΔ** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

| | Generali Sp | Generali Ti | Generali IP | OTP Abs | OTP EMDA | OTP G10 | OTP Supra | Platina Al | Platina Bé | Platina De | Platina Ga | Platina Pí | Raiff Hoz | Raiff Ind | Raiff Pan | Takarék In |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **DR(Ingersoll)** | -17.519 | -13.859 | -6.027 | -0.785 | 3.518 | 0.029 | 5.726 | 52.383 | 49.277 | -0.016 | 21.556 | 43.614 | -90.415 | -52.586 | -23.377 | -12.197 |
| **DR(Brown)** | -17.645 | -13.985 | -6.068 | -0.785 | 3.511 | 0.031 | 6.035 | 52.402 | 49.154 | -0.028 | 21.546 | 43.659 | -90.418 | -52.598 | -23.498 | -12.170 |
| **DR(Brown approx.)** | -17.645 | -13.985 | -6.068 | -0.785 | 3.511 | 0.031 | 6.035 | 52.402 | 49.154 | -0.028 | 21.546 | 43.659 | -90.418 | -52.598 | -23.498 | -12.170 |
| **DR(Ingersoll)-DR(Brown) Δ** | 0.1259 | 0.1265 | 0.0409 | -0.0001 | 0.0076 | -0.0013 | -0.3082 | -0.0190 | 0.1236 | 0.0116 | 0.0096 | -0.0449 | 0.0029 | 0.0121 | 0.1219 | -0.0271 |
| **DR(Ingersoll)-DR(Brown approx.) Δ** | 0.1259 | 0.1265 | 0.0409 | -0.0001 | 0.0076 | -0.0013 | -0.3082 | -0.0190 | 0.1236 | 0.0116 | 0.0096 | -0.0449 | 0.0029 | 0.0121 | 0.1219 | -0.0271 |
| **DR (Brown)-DR(Brown approx.) Δ** | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| **DR(Ingersoll)-DR(Brown) Δ%** | -0.7188 | -0.9125 | -0.6790 | 0.0081 | 0.2161 | -4.3789 | -5.3813 | -0.0363 | 0.2508 | -72.2744 | 0.0447 | -0.1029 | -0.0032 | -0.0229 | -0.5214 | 0.2219 |
| **DR(Ingersoll)-DR(Brown approx.)Δ%** | -0.7188 | -0.9125 | -0.6790 | 0.0081 | 0.2161 | -4.3789 | -5.3813 | -0.0363 | 0.2508 | -72.2744 | 0.0447 | -0.1029 | -0.0032 | -0.0229 | -0.5214 | 0.2219 |
| **DR(Brown)-DR(Brown approx.) Δ%** | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| **DR(Ingersoll) rank** | 23 | 22 | 19 | 17 | 12 | 15 | 11 | 1 | 3 | 16 | 7 | 4 | 29 | 28 | 24 | 21 |
| **DR(Brown) rank** | 23 | 22 | 19 | 17 | 12 | 15 | 11 | 1 | 3 | 16 | 7 | 4 | 29 | 28 | 24 | 21 |
| **DR(Brown approx.)rank** | 23 | 22 | 19 | 17 | 12 | 15 | 11 | 1 | 3 | 16 | 7 | 4 | 29 | 28 | 24 | 21 |
| **DR(Ingersoll)-DR(Brown)rankΔ** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **DR(Ingersoll)-DR(Brown app.)rankΔ** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **DR(Brown)-DR(Brown app.)rankΔ** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

**Table 19: Comparison of Doubt Ratio values calculated from Ingersoll et al. (2007) and Brown et al (2010) based MPPM values, as well as using Brown et al (2010) approximation.**

### 2.2.5. Comparison of the Ingersoll et al. (2007) and the Brown et al. (2010) method based on practical applicability and the complexity of their implementation, proposal for the preferred method

The calculations for the 31 Hungarian absolute return investment funds gave us insights into applicability and implementation difficulties, and the differences between the two methods in practical terms as well as and these are summarized in this chapter.

With respect to MPPM calculation, there is no major difference between the two approaches as regards difficulty or the necessary calculation steps. While the Ingersoll et al. (2007) formula takes the average of the *risk-adjusted return premiums* in the period, and then adjusts it with a logarithm and the risk aversion factor, the Brown et al. (2010) approach calculates using the simple difference of the *average excess returns* in the period and the variance, where the risk aversion factor is included as the coefficient of variation. So the Brown et al. (2010) approach uses an additional step when calculating the variance of excess returns, and this facilitates the better understanding of the logic behind the MPPM structure by quantifying risk. Since the Brown et al. (2010) MPPM is a linear approximation of the more accurate Ingersoll et al. (2007) MPPM, and according to the calculations there are differences between the two methods that influence ranking, the Ingersoll approach should be used to calculate MPPM. The calculation of the Brown et al. (2010) MPPM or the steps necessary for that are recommended if the analysis also seeks to find out the average and standard deviation of excess return to ensure the better understanding of the correlations.

The calculation of the Doubt Ratio includes the same steps using both the Ingersoll et al. (2007) and the Brown et al. (2010) MPPM values (or the Brown et al. (2010) approach to approximate the Doubt Ratio); therefore, they require exactly the same effort. Taking into account the observed inaccuracy of the Brown et al. (2010) MPPM formula arising from the linear approach, the Doubt Ratio can be more accurately calculated from the Ingersoll et al. (2007) MPPM, and therefore the use of the latter is recommended.

# 3. SUMMARY

In the dissertation in the summary of the literature and methodology (Chapter 1) we have introduced connected to our first examined topic, the examination of price reactions around company reports, the literature of market efficiency and its critiques, moreover the tools that can be used to test market efficiency, the methodology of event study. We have presented in relation to our examined second topic, in connection to the observable performance manipulation of the reports of investment funds, the development of performance measures, and the measures developed to tackle performance manipulation, and also the manipulation detecting measure formed from them, and other manipulation detecting methods and techniques.

In Chapter 2, which summarizes our own calculations, we first analysed the price effects around listed companies' quarterly reports, examining the strength of market efficiency by measuring the presence of abnormal returns around the publication of quarterly reports. To do this, we have analysed samples from the 45-45 largest members of the S&P 500 and S&P 500 IT indices (for which we had complete data), with samples consisting of 16 quarterly reports and 720-720 items. We divided the samples into further subgroups according to which surprises in earnings per share represent very good, good, neutral, bad or very bad news for the market.

We have accepted the first statement of our first hypothesis: The direction and magnitude of corporate profitability surprises determine how stock prices change as a result of corporate reporting. At the same time, a shift can be seen in the level and direction of cumulative abnormal returns perceived by each newsgroup towards negative price reactions, thus a significant positive return occurs only in the very good news group, while the good news group no longer has a significantly different return from 0, whereas the neutral news group shows negative cumulative abnormal returns but in the bad and very bad news group its magnitude is greater than that of can be experienced in the neutral group.

However, the second statement of our first hypothesis is rejected the effect of the new information can no longer be observed on the trading days following the announcement and no trend develops appropriate to the surprise (moreover, in the very good news group of the

S&P 500 a significant price correction can be seen). Thus, the analysis confirms that the market for stocks in the selected sample is moderately efficient.

Significant negative abnormal returns on neutral news may be explained by the fact that the sample comes from an economic cycle of upturn when company results that “only” meet expectations may also be negatively received by market participants.

There is a significant difference between the cumulative abnormal returns of the S&P 500 and S&P 500 IT indices around quarterly reports at the usual significance levels in the very good, very bad and neutral news groups, and in the S&P 500 IT newsgroups, the cumulative abnormal returns are higher between the two indices. In the good and bad news groups, however, there is no significant difference in the amount of abnormal returns experienced between the two indices. In case of the good news group, this is not a surprising development given that in both cases we saw not significantly different returns from 0 in the earlier part of the analysis in this news group, and considering that due to the shift towards negative price reactions this news group can be reckoned as the reference point among news groups. Based on the results, we generally agree with hypothesis 2 formulated in the chapter that the impact of surprise on prices is stronger in the technology sector compared to the general stock market.

The second market failure we investigate, return and performance manipulation around investment fund managers' reports or bias due to suboptimal investment decisions in returns through which the investment manager consciously or unconsciously is able to improve his *detected* performance by classical measures by knowing the performance indicators used for evaluation, although he does not have any additional ability, knowledge, or information to create real added value, additional risk-adjusted return, and thereby increase the utility of the rational investor who owns the units of the fund. Although in most cases performance manipulation is neither a fraud nor an illegal act, but as a result of misleading investment fund management activities, not only can the management activities become suboptimal, but also the distribution of resources through investment fund management to companies, which ultimately entails high social costs. To detect traces of performance manipulation or suboptimal investment decisions, we used Manipulation Proof Performance Measures (MPPMs), the manipulation detecting indicator formed from them, the Doubt Ratio, and other alternative methods and indicators such as the Bias Ratio and discontinuity analysis. Our analysis is a new result, as there is no known example of tracing of return manipulation in the literature for Hungarian investment funds. For the purposes of our calculations, we used daily prices from a Hungarian absolute return funds over a 7-year period. According to our results, the rank-correlations between MPPM and Sharpe-ratio are in the range of 0.76-0.82, which is higher than the range around 0.7 of international examples, but indicates a level of deviation from classical measures that may be caused by some level of return manipulation or return smoothing.

As a new result, we have compared MPPM and the Doubt Ratio values and rankings calculated with the Ingersoll et al. (2007) and Brown et al. (2010) formulas. We have presented that the Ingersoll et al. (2007) and Brown et al. (2010) based MPPM and Doubt Ratio results are almost overlapping, and we investigated how the small number of differences experienced can be explained. The results prove that the linear approximation of the MPPM by Brown et al. (2010) less penalizes risk relative to Ingersoll et al. (2010). The larger value changes observed in MPPM between the Ingersoll et al. (2007) and Brown et al. (2010) methods are generally inherited further magnified into the Doubt Ratio, calculated from them. An order change between the two methods is found between both the MPPM and the Doubt Ratio, if the change experienced is large enough and the values of the surrounding funds are close enough so that the change in value can affect the order.

Since, there is no significant difference between Ingersoll et al. (2007), and Brown et al. (2010) formulas in the difficulty of calculating MPPM and the number of steps required in terms of runtime, and since Ingersoll et al. (2007) MPPM is only a linear approximation of Brown et al. (2010), which is sometimes inaccurate also in order, therefore we recommend the calculation of MPPM using the more precise method of Ingersoll et al. (2007). Brown et al. (2010), however, may be advantageous to calculate the mean and standard deviation of the excess return for analytical purposes. Another new result is that, according to our own calculations, although the Doubt Ratio was built by Brown et al. (2010), it is still worth using the version which is based on the Ingersoll et al. (2007) MPPM, as it provides more accurate results, so we recommend using it.

A further new result of our own calculations contributing to the literature, is that, contrary to the close overlap of the Doubt Ratio with other return manipulation detecting methods (80% match according to Brown et al. (2010)), our analysed sample showed mixed results, as alternative methods indicated anomalies in 10 out of 31 investment funds, that is, return manipulation with high probability, while the Doubt Ratio flagged only 4 investment funds as suspicious. We found signs of discontinuity too around 0 in risk adjusted returns for the former in 4 cases, while for the later in 1 occasion.

Overall, therefore, according to our results, the Bias Ratio has proved to be a better pre-screening tool for more detailed analysis of return manipulation (e.g. with discontinuity analysis) than the Doubt Ratio. However, it should be noted, that the Doubt Ratio could only be used by identifying outliers in the analysed sample since no investment fund has reached the critical value of 150, and the analysis has been conducted on a relatively small sample, it cannot be considered generally proven that this difference would appear the same in larger samples.

Based on investment policies and interviews with investment managers, only in case of one fund, the Concorde Citadella seem suspicious signals well founded, and this fund was marked as suspicious by both the Doubt Ratio and the Bias Ratio. In case of this fund, the existence of distortion due to sometimes sub-optimal investment decisions seems well founded in the knowledge of investment policy.

We have also taken a new approach when separating suspicious investment funds using a graphical representation of striking deviations from the group average for both the Doubt Ratio and the Bias Ratio. As an innovation we recommend using the following protocol to filter performance manipulation: 1. The discontinuity analysis of investment funds with a Doubt Ratio of more than 150, and the assessment of the Bias Ratio according to the median rule. 2. A graphical representation of the values of the Bias Ratio and Doubt Ratio in the Bias Ratio-Doubt Ratio space and, subsequently based on the deviation from the group average, the discontinuity analysis of the returns of investment funds that appear to be outliers. 3. Discontinuity analysis of investment funds with Bias Ratios higher than the median. 4. An overview of investment policies to understand the underlying investment decisions that can strengthen or refute the potential existence of suboptimal decisions, or weaken the reliability of statistical methods, for example if the composition of the investment fund is overweighed with fixed-income assets, or when the fund operates as fund of funds and always allocates the vast majority of its capital into investment funds.

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