Investors' Reactions to Extreme Events in the Hungarian Stock Market*

Klaudia Rádóczy – Ákos Tóth-Pajor

This paper examines investors' reactions to extreme events in the Hungarian stock market. We seek to answer the research question whether following extreme events any overreaction of investors can be observed on the Budapest Stock Exchange. With a view to answering the research question, we identify extreme events based on extreme returns on the market portfolio and then – using an event study – we examine abnormal returns on winner and loser equities. After examining investors' reactions, we inspect the performance of the contrarian strategy in the created event windows. The main result of our research is the presentation that – based on the analysis of the differences between the average cumulative abnormal returns after extreme events – investor overreactions can be observed in the Hungarian stock market. The loser portfolios relating to extreme events significantly outperform winner portfolios connected to the event. The excess return of the contrarian strategy cannot be attributed to differences in the market risk of winner and loser portfolios. The excess return of the strategy can be shown only under tighter extreme value thresholds. The clustering of the event windows with short-term reversal, high market volatility and extreme events is beneficial to the performance of the contrarian strategy. In addition, our research also shows that the purchase of loser portfolios or the development of a contrarian strategy after extreme events may generate profit for investors, since after extreme events the loser portfolios usually beat the market on a horizon of 21 days.

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1. Introduction

The purpose of this paper is to analyse investors' reactions to extreme events in the case of equities traded on the Budapest Stock Exchange. We identified extreme events based on the daily returns of the market portfolio that exceeded the salient returns of the market portfolio that could be identified in the prior period. The research aims to find out whether any investor overreaction can be observed as a result of extreme events in the Hungarian stock market. The research heavily relies on the work of *Piccoli et al.* (*2017*), who examined investors' reactions to extreme events in the stock market of the United States. In their work, they presented the results of the contrarian investment strategy in periods after extreme events, relying on an event study. Similar studies were conducted for Hungary by *Nagy – Ulbert* (*2007*) and *Lakatos* (*2016*), but their research did not focus on extreme events. This paper's value added to Hungarian stock market analyses is the analysis of reactions to extreme events.

Major corrections can often be seen in stock markets, but when the market gains momentum, extreme positive returns are not uncommon. Crisis periods are a good example of corrections. During the 2008 global economic crisis, corrections of around 20 per cent could be observed, while in 2020 – after the outbreak of the Covid-19 pandemic – corrections as high as 50 per cent were not uncommon in stock markets. The investment strategy examined by us may provide investors with favourable performance during these turbulent periods.

In the research, extreme events are defined based on extreme returns of the market index, and then – relying on an event study – we examine the abnormal returns on winner and loser equities following the event. If in the period that follows the defined extreme event loser equities significantly outperform the winner equities, investors' overreaction can be confirmed and the contrarian investment strategy may be profitable.

Our results show that investors in the Hungarian stock market overreact to extreme events. There are significant differences between winners and losers. The excess return of the contrarian strategy does not come from the differences between the market risks of the loser and winner portfolios. The excess return also exists with the factors underlying the systematic risk.

The paper first reviews the international literature relevant for the topic and then presents the results of Hungarian stock market research. After laying down the theoretical foundation, relying on the methodology of *De Bondt – Thaler* (*1985*) and *Piccoli et al.* (*2017*), we perform a comprehensive analysis of the Hungarian stock market for the period from 4 January 2000 to 12 March 2021.

2. Investors' overreactions in the stock markets

Fama's (*1970*) theory of efficient markets (Efficient Market Hypothesis) states that the capital market is efficient when information is immediately incorporated into the price of assets. In the case of capital markets, a semi-strong level of efficiency is most often observed, which assumes the incorporation of public information into asset prices. If this is accepted, investors cannot have information that would allow them to realise excess returns. Higher returns can only be achieved by taking higher risks. If the risk of the investment strategy corresponds to the risk of the market portfolio, it is impossible to beat the market. If market efficiency based on the CAPM[1] model exists, the observed differences in returns stem from the difference in market risk.

According to the Uncertain Information Hypothesis, *Brown et al.* (*1988*) argue that positive abnormal returns can be observed in stock markets over a 60-day period following daily price changes of more than 2.5 per cent, after both negative and positive events. This phenomenon supports the Efficient Market Hypothesis, because according to the hypothesis positive abnormal returns are simply attributable to the increase in risk after the events. If the Uncertain Information Hypothesis is valid, abnormal returns should disappear when the risk is taken into consideration. According to the hypothesis, abnormal returns should appear following both positive and negative events. *Corrado – Jordan* (*1997*) believe that the 2.5 per cent threshold is far too low. The authors found that the market reverses if a 10 per cent threshold was applied.

In their paper, *De Bondt – Thaler* (*1985*) examined underperforming and outperforming equities relative to market returns in distinct observation periods (without overlapping periods). Their fundamental assumption was that investors misprice equities in stock markets, despite the expected value of conditional probabilities (Bayes' theorem), possibly overreacting to the value of the new information believed to be unique. Their main finding is that securities that performed poorly earlier will outperform securities that performed better in the past by about 25 per cent in the future. This phenomenon is the overreaction, which essentially disproves *Fama's* (*1970*) Efficient Market Hypothesis. *De Bondt – Thaler* (*1985*) explained the phenomenon of overreaction by the fluctuating nature of the positive and negative information environment, and linked it to *Kahneman – Tversky's* (*1979*) overconfidence theory, according to which investors are overly confident when it comes to forecasting future prices, i.e. they believe that their investment decision will have a positive outcome in the future. *De Bondt – Thaler* (*1987*) also confirmed the Overreaction Hypothesis in their work 2 years later, and *Daniel et al.* (*2004*) also use this hypothesis to explain specific return patterns.

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[1] Capital Asset Pricing Model

Shiller (*1981*) also dealt with the possibility of the Overreaction Hypothesis; however, he referred to the phenomenon when securities market investors overreacted to certain events or announcements as "excess volatility". The Overreaction Hypothesis has been tested successfully on a number of occasions in several markets.

Alonso – Rubio (*1990*) examined the Overreaction Hypothesis in the Spanish stock market. According to the results, the phenomenon can be definitively identified. The portfolios created based on *De Bondt – Thaler* (*1985*) realise a profit that is 24.5 per cent higher 12 months later for the loser portfolios, as compared to the winners. In the German stock market, *Ising et al.* (*2006*) examined the 100 largest companies for which the equity price change between 1990 and 2003 exceeded a negative or positive value of 20 per cent. According to their results, reactions after large price rises support the Overreaction Hypothesis, while there is underreaction to the subsequent price decrease. *Chan* (*1988*) points out that the Overreaction Hypothesis is very susceptible to the applied methodology. In his research, he applied risk corrections in the CAPM model.

The reversal shown by *De Bondt – Thaler* (*1985*) (i.e. the formerly loser portfolio outperform previously winner portfolios) is also referred to in the literature as winner-loser effect, which is in fact the foundation of the contrarian or counter-strategy. However, if the reversal does not occur, i.e. winner portfolios continue to realise high returns, it is advisable to apply the momentum strategy. With the contrarian strategy, we buy loser portfolios and short sell winner portfolios, while it is just the opposite with the momentum strategy.

Of the research related to the momentum strategies, *Jegadeesh – Titman* (*1993*) were the first to state that the price of equities that rose in the past is likely to rise in the future as well, and vice versa. After this, several empirical studies were built on proving both the reversal and overreaction hypothesis together with the related strategies and on identifying them in a variety of markets.

Pham et al. (*2008*) tested the overreaction hypothesis in the Pacific markets over the period 2001 to 2005. They examined the effects of price changes over short (3-day) and long (20-day) periods. Their research was able to validate both the short-term reversal and the overreaction hypothesis in the emerging market of Vietnam and in the developed Japanese and Australian markets. *Himmelmann et al.* (*2012*) examined the major European stock markets based on the EuroStoxx 50 index. Their paper supports the efficient market hypothesis as they found that large price rises and falls are usually followed by average market returns.

Brooks – Persand (*2001*) identified market anomalies with good results when they analysed five Southeast Asian stock exchanges. *Chan* (*2003*) tried to explore reactions to different news. His results show strong sideway drift after bad news,

with investors reacting slowly. On the other hand, he links the reversal linked to extreme price fluctuations to public news. *Hart et al.* (*2003*) underpin the reality of excess return realisable by applying the momentum strategy. They tested the theory on multivariate strategies with a positive result.

Examining the stock markets of the United States, the United Kingdom and Japan, *Hudson – Atanasova* (*2008*) found that future returns depend on the magnitude and sign of previous price changes, but the effect gradually diminishes. After large price changes the market often turns around, while a momentum strategy is advisable in the case of small price changes.

The literature shows that loser portfolios outperform winner portfolios over a horizon of 1–4 weeks. The contrarian strategy may be profitable over this horizon, while in the case of the momentum strategy winner portfolios outperform loser portfolios over a horizon of 12 months (*Jegadeesh – Titman 1993*). The reversal effect can also be observed over the longer horizon of 3–5 years (*Brown – Harlow 1988*). When the transaction costs are also taken into consideration, investors give preference to investment strategies of longer cycle. The reversal effect can be detected in the case of larger, extreme price changes.

There is evidence of market anomalies, which prejudice the sometimes weak, sometimes medium and sometimes strong level of market efficiency, thereby facilitating insider trading, various trading strategies and also the development of stock market bubbles (*Deev et al. 2019*). However, back in 1998 *Fama* (*1998*) also argued that proven market anomalies appear depending on the applied methodology and they are often a mere coincidence.

In their work, *Piccoli et al.* (*2017*) examined the period between 1926 and 2013 based on the daily returns on the equities included in the S&P 500, using the event study methodology. Having examined investors' reactions to extreme events, they point out that investors' overreaction in the US stock market can be observed after extreme events. After the events, loser equities outperform winner securities. As a result of the overreaction, the contrarian investment strategy may generate profit for investors.

Yuan (*2015*) highlights the fact that high-profile events, such as record highs in market indices, forecast investors' behaviour and returns. When the market index is high, a high-profile event tends to prompt investors to sell equities, which has a negative impact on prices.

In their work, *Baltussen et al.* (*2019*) argue that systematic risk explanatory factors, well-known from asset pricing, based on cross sectional differences, are present regardless of the asset class and are able to explain changes in risk premiums, and thus the momentum effect can also be deemed significant. On the other hand, the

work of *Piccoli et al.* (*2017*) shows that the presence of extreme events rather calls for the contrarian strategy in the short run, due to investors' reactions.

Since Hungary is a small, open economy, the bulk of its stock market turnover is constituted by a few securities. In addition, its liquidity is also low. A large part of Hungarian households invest their capital in domestic securities due to liquidity considerations. From the 1990s to the 2000s, several papers examined the efficiency, anomalies and returns of the Budapest Stock Exchange, reinforcing the legitimacy of the domestic securities market (*Rappai* (*1995*), *Grubits* (*1995a;1995b*), *Andor et al. (1999)* and *Lukács* (*2003*)). *Molnár* (*2006*) also analysed market efficiency, summarising the research on the efficiency of the Hungarian stock market. Having reviewed two decades of efficiency research related to the Hungarian market, he concludes that signs of market inefficiency can be identified on the Hungarian stock exchange, but those are not yet sufficient for developing trading strategies capable of realising stable extra return.

Stock market anomalies in the Hungarian stock market were analysed by *Nagy – Ulbert* (*2007*). In their study, they tested the hypothesis of momentum and reversal in addition to systematising stock market anomalies. Their study focused on the periods 1999–2001 and 2005–2007 and included nine equities. The analytical framework was based on the methodology developed for the winner and loser portfolios by *De Bondt – Thaler* (*1985*), but their analysis also integrated the effect of dividends in the returns. Their results show very significant reversal phenomenon in the periods under review. They explain the fact that loser securities outperform previously winner securities in the longer run resulted by investors' mental accounting and connect it to the overreaction hypothesis.

In his paper, *Lakatos* (*2016*) observed the winner-loser effect of De Bondt and Thaler on the Budapest Stock Exchange. In his analysis, he examined domestic Class "A" and Class "B" securities with outstanding turnover between December 1996 and March 2015. His results show that the phenomenon of overreaction can be observed on Budapest Stock Exchange. Over a longer horizon, previously loser portfolios outperform the previously winner portfolios, i.e. the reversal phenomenon can be also observed in the market. He also highlights the fact that the anomaly identified by the study seems to disappear towards the end of the period, i.e. the difference between the abnormal returns of the winner and loser portfolios ceases to exist. Taking his research further, he examined periods of varying lengths, which showed that overreaction can be observed in the case of short periods, but there is no reversal.

Other research on the domestic securities market also touched upon the momentum strategy. In their paper, *Mérő et al.* (*2019*) reviewed the importance of factor models, and their empirical test confirmed that the momentum effect can

significantly explain future returns in the Hungarian stock market as well. Taking their paper further, *Csillag – Neszveda* (*2020*) proved that in the period between 1996 and 2018 companies that performed well in the past significantly outperform the returns of poor performing companies in the future as well.

Based on the review of the literature, we can state that investors' overreaction can be observed in the stock markets of both the United States and Hungary.

In the following, we examine two research questions that can be tested empirically as well. On the one hand, we seek to answer the question whether following extreme events any overreaction of investors can be observed in the Hungarian stock market. On the other hand, we examine whether the contrarian strategy can be profitable after extreme events. Based on our preliminary expectations, we formulated the following assertions:

1. Following extreme events, loser equities significantly outperform winner equities, which implies investors' overreaction.

2. Following extreme events, the application of the contrarian strategy generates profit.

3. Sample and descriptive statistics

Data for the empirical examination were collected from the Refinitiv database. As a starting point for our analysis, we downloaded the daily closing price data of equities traded on the Budapest Stock Exchange and the BUX index for the period from 29 December 1999 to 12 March 2021. The Refinitiv database contains price data for 43 equities listed in Hungary. Of the available data, we included in the empirical analysis equities for which the time series is complete, i.e. in the period under review they were available for trading on the Budapest Stock Exchange. As an additional selection criterion, only those equities were included in the sample for which the number of contiguously missing daily closing prices did not exceed 8 pieces of data. This selection criterion ensured that only the more liquid traded equities were included in the analysis. The selection of the sample is based on the work of *De Bondt – Thaler* (*1985*), where the criterion for the inclusion of equities in the sample for review is that a certain number of contiguous returns is available for them. Thus, the sample facilitated the analysis of larger companies with high turnover, also responding to the criticism that losers may have excess return because there are smaller companies among them. *Banz* (*1981*) argues that the equities of companies with low market capitalisation generate disproportionately high returns compared to companies with high market capitalisation. *Zarowin* (*1990*) also argues that overreaction is attributable to differences in size. In selecting the sample, we made efforts to include in the sample only equities that may be

a relevant investment target for investors. Filtering the data left us with 9 equities in the sample in total. *Nagy – Ulbert* (*2007*) also worked with a sample of similar size in their domestic stock market research. On trading days when a particular equity was not traded, the closing prices were substituted for the last known closing price.

Table 1

Descriptive statistics of daily returns

	Average (per cent)	Standard deviation (per cent)	Risk-adjusted return (per cent)	Cumulative return (per cent)	Number of observations
BUX	0.041	1.486	0.028	395.63	5,289
Richter	0.047	1.824	0.026	409.639	5,289
MOL	0.044	2.053	0.021	238.286	5,289
MTelekom	−0.013	1.701	−0.008	−76.836	5,289
Nutex	0.005	5.364	0.001	−99.921	5,289
OPUS	0.086	4.263	0.02	−11.074	5,289
OTP	0.069	2.338	0.03	806.694	5,289
PannErgy	0.014	2.112	0.007	−34.455	5,289
Rába	0.01	2.093	0.005	−45.416	5,289
Zwack	0.026	1.454	0.018	127.805	5,289

In *Table 1* we present the descriptive statistics of daily returns. The daily returns were calculated from the daily closing prices for the period from 1 January 2000 to 12 March 2021. The average daily return of the BUX index, used as market benchmark, was 4.1 basis points in the period under review, with a standard deviation of 1.486 per cent. The average daily return of Richter Gedeon and MOL were similar to the market return, while OPUS and OTP outperformed the market. In terms of cumulative returns in the period under review, BUX – with a cumulative performance of 395.63 per cent – registered almost 4-fold growth, while OTP registered 8-fold growth.

In *Table 2* we present the descriptive statistics of daily abnormal returns calculated for the event study. Abnormal returns are defined as the difference between the daily returns on equity and the market return (market-adjusted excess return). We chose this method, because the explanatory power of proven asset pricing models (market model, CAPM) was acceptable only for blue chips (Richter, MTelekom, MOL, OTP). In the case of other equities the explanatory powers obtained were very low.

Table 2

Descriptive statistics of daily abnormal returns

	Average (per cent)	Standard deviation (per cent)	Risk-adjusted abnormal return (per cent)	Cumulative abnormal return (per cent)	Number of observations
Richter	0.006	1.46	0.004	−21.372	5,289
MOL	0.003	1.279	0.002	−24.86	5,289
MTelekom	−0.054	1.44	−0.038	−96.77	5,289
Nutex	−0.036	5.332	−0.007	−99.99	5,289
OPUS	0.045	4.267	0.011	−90.122	5,289
OTP	0.028	1.357	0.02	165.868	5,289
PannErgy	−0.027	2.273	−0.012	−93.894	5,289
Rába	−0.031	2.106	−0.015	−93.939	5,289
Zwack	−0.015	1.917	−0.008	−83.066	5,289

In *Table 2* we can observe positive average daily market-adjusted excess return for Richter, MOL, OTP and OPUS. While OTP outperformed the market by an average of 2.8 basis points, OPUS outperformed the market by an average of 4.5 basis points per day. When examining the cumulated abnormal returns, it is clear that only OTP was able to outperform the market. OTP's cumulated abnormal return in the period under review is 165.87 per cent.

In the next step, since the purpose of this paper is to examine investors' reaction to extreme events, we looked for positive and negative extreme events in the Hungarian stock market. For this purpose, we used the methodology applied by *Piccoli et al.* (*2017*). We defined extreme events not on the basis of excess return on equities, but rather based on the excess return of the BUX index, used as market portfolio. Extreme events are events when the daily return of the market portfolio exceeded the extreme returns of the market portfolio observed in the previous period. Market portfolio returns were measured by the daily returns of the BUX index.

We compared the returns of the index observed at time t^{th} with the BUX index returns on the 500 trading days prior to time t^{th} belonging to the 1st and 99th percentiles of the empirical density function, defining the extreme large positive and negative returns in this way. This procedure corresponds to the Value at Risk estimated by a historic simulation in the long and short position. This implies that the 99th percentile of the empirical density function determines the short position's value at risk, while the 1st percentile of the same distribution determines the long position's value at risk. According to our calculations, in the period under review the daily returns below the 1st percentile constitute the extreme negative

events of the period, while the daily returns over the 99th percentile constitute the extreme positive events of the period. Accordingly, the tested sample allowed the identification of extreme events between 7 January 2002 and 12 March 2021.

Table 3			
Annual distribution of the identified extreme events			
Year	**Number of trading days**	**Number of negative extreme events**	**Number of positive extreme events**
2000	251	n/a	n/a
2001	245	n/a	n/a
2002	249	2	1
2003	250	1	0
2004	254	1	2
2005	253	6	4
2006	252	2	5
2007	245	2	1
2008	251	12	9
2009	251	0	0
2010	254	1	1
2011	253	3	3
2012	244	0	0
2013	246	1	0
2014	248	3	4
2015	249	2	5
2016	252	3	1
2017	251	0	1
2018	244	4	7
2019	246	0	0
2020	251	10	9
2021	50	0	0
Number of observations	**5,289**	**53**	**53**

We identified 106 extreme events in total, of which negative extreme returns and positive extreme returns were observed in 53 cases each. The highest number of extreme events was observed in 2008 and 2020 (*Table 3*). These two years can be considered as crisis years. In the two crisis years, in addition to the higher number of events, the number of negative and positive extreme events is almost the same. 41.5 and 34 per cent of all identified negative and positive extreme events, respectively, can be linked to these two years.

Figure 1
Positive and negative extreme returns on the market portfolio
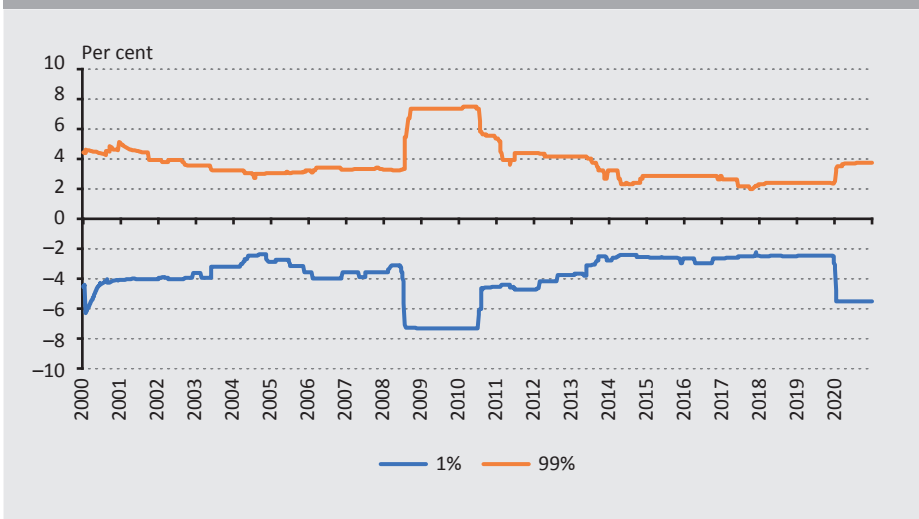
In *Figure 1* we show the extreme daily returns of the BUX index – applied as a market portfolio – calculated using the 500-day rolling VaR method. The figure illustrates the 1st and 99th percentiles belonging to the empirical density function of the BUX returns observed during the 500 trading days prior to time t^{th}. Figure 1 clearly shows that during the 2008 global economic crisis volatility in the Hungarian stock market was higher, which also increased the extreme values of daily returns. The same phenomenon can be observed in spring 2020 as well, i.e. the period of the Covid-19 pandemic.

4. Investors' overreactions after extreme events in the Hungarian stock market

After identifying extreme events, we examined investors' reaction using an event study. After defining the extreme event, we created a 21-day time window for each of the 106 events for the event study. For each event window, we constructed winner and loser portfolios according to the abnormal returns observed on the day of the extreme event, relying on the methodology of *De Bondt – Thaler* (*1985*), with equal weighting. The 9 analysed equities were ranked according to the abnormal return observed on the day of the event for each event window, and then the equities in the upper tercile and in the lower tercile were allocated to the winner and loser portfolios, respectively. If the loser portfolios significantly outperform the winner portfolios in the period after the extreme event, it may imply investors' overreaction.

The allocation of equities to portfolios in this manner differs from that applied by *Lakatos* (*2016*), but it is in line with the work of *Piccoli et al.* (*2017*), who argue – following *Brooks et al.* (*2003*) *and Coleman* (*2012*) – that the market reaction to unexpected events is determined on the day when the event occurs. It should be noted that while *De Bondt – Thaler* (*1985*), *Nagy – Ulbert* (*2007*) or *Lakatos* (*2016*) determined the various test periods as non-overlapping periods, in our case certain time windows in the years of the crisis may overlap due to their rate of occurrence and higher frequency. Extreme events cannot be considered as independent of each other; accordingly, we also performed the analysis, following the work of *Piccoli et al.* (*2017*), on subsamples with no overlap and with different combinations of events.

After classifying the equities, we calculated the abnormal returns on the winner and loser portfolios based on equation (1).

$$AR_{n,j,t} = \sum_{i=1}^{k} w_{n,i,j} AR_{i,t} \tag{1}$$

where $AR_{n,j,t}(T)$ is the abnormal return of the portfolio j (winner or loser) of the nth event window on day t^{th}, $w_{n,i,j}$ is the weight of equity i^{th} in portfolio j^{th}, which is the same on each day of the nth event window, $AR_{i,t}$ is the abnormal return on equity i^{th} on trading day t^{th}.

Using the above formula, we obtain the same result as if we calculated the returns on the winner and loser portfolios and then took their difference with the returns of the BUX index. Thus, the abnormal return definition we used allows us to create an equivalent definition of the abnormal returns on winner and loser portfolios based on the above formula.

After creating the winner and loser portfolios, the next step was to calculate the cumulative abnormal returns. In equation (2) $CAR_{n,j}(T)$ shows the (j) cumulative abnormal return on (n) winner or loser portfolio of the given event window on the Tth day of the event window, while $AR_{n,j,t}$ denotes the abnormal returns on portfolio j^{th} (winner or loser) of event window n^{th} at time t^{th} of the event window.

$$CAR_{n,j}(T) = \sum_{t=0}^{T} AR_{n,j,t} \quad T = 1,2,\dots,21 \tag{2}$$

After defining the cumulative abnormal returns, we calculated the average cumulative abnormal returns based on equation (3), aggregating it separately for the loser and winner portfolios, i.e. we derived the average cumulative abnormal returns on the aggregated winner and loser portfolios for time T^{th} of the event window as follows.
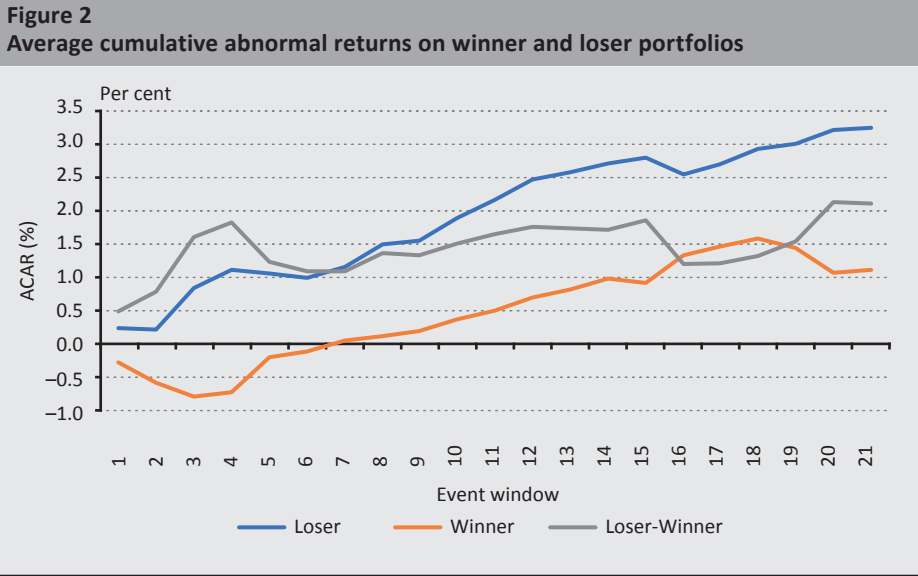
$$ACAR_j(T) = \frac{\sum_{n=1}^{N} CAR_{n,j}(T)}{N} \tag{3}$$

After calculating the average cumulative abnormal returns, we took the difference between the average cumulative abnormal return on loser portfolios and the average cumulative abnormal returns on winner portfolios based on equation (4). The significant positive difference in the averages of the cumulative abnormal returns implies the overreaction of investors.

$$ACAR(T)_{dif} = ACAR(T)_{loser} - ACAR(T)_{winner} \tag{4}$$

The methodology presented here is based on the work of *De Bondt – Thaler* (*1985*) and *Piccoli et al.* (*2017*). Of the two works referred to above, it was the work of *Piccoli et al.* (*2017*) that applied the methodology to the analysis of extreme events. Their paper analysed the US stock market and their results show that the overreaction hypothesis can be confirmed in investors' reactions also when making decisions on extreme events.

Figure 2 shows the averages of cumulative abnormal returns for the 21-day event window following extreme events. It illustrates the average cumulative abnormal returns on the created winner and loser portfolios for 106 extreme events. The figure clearly shows that after extreme events loser portfolios outperform winner portfolios. While winner portfolios perform below the market return for 6 days after the extreme event, the average cumulative abnormal returns on loser portfolios are positive. The average cumulative return on winner portfolios is once again positive on the 7th trading day. These results are in line with the conclusions of *Piccoli et al.* (2017). However, it should be noted that the reactions to extreme events in the Hungarian stock market are less pronounced than the results presented by the authors in relation to the US stock markets.

Figure 2
Average cumulative abnormal returns on winner and loser portfolios

The differences between the average cumulative abnormal returns of the loser and winner portfolios are presented in *Table 4.* The significant positive differences suggest that loser portfolios outperform winner portfolios, which implies that investors overreact after extreme events. When examining the contrarian strategy, i.e. buying loser portfolios and short selling winner portfolios, we find that on average significant positive abnormal returns can be realised in the Hungarian stock market compared to the market portfolio. After extreme events, the contrarian investment strategy may generate profit for investors in the short term.

Table 4
Differences between the average cumulative abnormal returns

Event window	Loser ACAR (per cent)	Winner ACAR (per cent)	Loser-Winner (per cent)	t-test
1	0.243	−0.326	0.568***	19.633***
2	0.278	−0.654	0.931***	24.121***
3	0.945	−0.843	1.788***	38.298***
4	1.261	−0.759	2.020***	34.224***
5	1.263	−0.178	1.441***	21.883***
6	1.240	−0.063	1.303***	19.280***
7	1.425	0.139	1.285***	17.834***
8	1.775	0.193	1.581***	21.668***
9	1.861	0.337	1.524***	21.193***
10	2.212	0.524	1.688***	22.805***
11	2.459	0.679	1.780***	21.450***
12	2.727	0.865	1.863***	21.111***
13	2.832	0.984	1.848***	20.522***
14	3.003	1.181	1.823***	19.663***
15	3.084	1.116	1.968***	20.541***
16	2.816	1.495	1.320***	13.204***
17	3.007	1.627	1.379***	13.152***
18	3.215	1.752	1.463***	13.766***
19	3.352	1.631	1.721***	15.925***
20	3.535	1.210	2.325***	20.690***
21	3.580	1.296	2.284***	19.820***

*Note: Asterisks at the differences represent the p-values from the Wilcoxon test. ***p < 0.01, **p < 0.05, *p < 0.1.*

5. Performance of the contrarian strategy in the analysed event windows

Following the analysis of investor reactions, we also examined the performance of the contrarian strategy in the event windows after extreme events. With the contrarian strategy, we take long positions in loser portfolios and short sell winner portfolios. In this way, we expect that after the extreme events loser portfolios may outperform winner portfolios, and thus this strategy may help us realise a profit.

When examining the performance of the contrarian strategy, following the method of *Piccoli et al.* (*2017*), we sorted the returns on the winner, loser, contrarian and market portfolios in a panel dataset for 21 days of the event windows created during the analysis of the extreme events. Following this, we examined whether the portfolios thus created also earned excess returns over the market risk premium. We determined the portfolios' beta and Jensen alpha indicators based on the equations of the CAPM model using Pooled OLS estimation. In the paper, we examine the performance of the portfolios in terms of market efficiency based on the CAPM model. Finding a positive significant Jensen alpha indicator in the case of the contrarian strategy implies that that excess return of the strategy is not generated by the difference in the market risk of the loser and winner portfolios. We estimated the Jensen alpha of the contrarian portfolio based on equation (5). The market risk premium was defined as the difference between the BUX index and the 1-year zero-coupon return converted into an overnight return. Zero-coupon risk-free return in the Refinitiv database was available only from 7 March 2002, and thus it was possible to include all 106 events in the analysis. This allowed us to perform an ex-post assessment of the portfolios' performance after the event. At the time of the extreme event this information is not yet known for the investors, since then neither the time of all events nor the market risk premium rate are known.

$$R_{L,i,t} - R_{W,i,t} = \alpha + \beta \cdot (R_{M,i,t} - R_{f,i,t}) + \varepsilon_{i,t} \qquad (5)$$

where $R_{L,i,t}$ is the return on loser portfolios, $R_{W,i,t}$ is the return on winner portfolios, $R_{M,i,t}$ is the return of the BUX index, $R_{f,i,t}$ is the 1-year zero-coupon return calculated for one day, α is the Jensen alpha, β is the ex-post market risk, $\varepsilon_{i,t}$ is the error term, and *i* is used for the indexation of the extreme events, while *t* for the indexation of the days in the event window.

Table 5
Estimation results of the CAPM model

Samples	Parameters	Loser-Winner	Loser	Winner
Full	α (%)	0.122** (0.051)	0.134*** (0.045)	0.012 (0.033)
	β	0.082 (0.084)	0.772*** (0.043)	0.690*** (0.046)
	Adjusted R^2 (%)	0.582	52.786	51.851
	Number of observations	2,226	2,226	2,226
Negative extreme events	α (%)	0.157** (0.072)	0.148** (0.068)	−0.009 (0.045)
	β	0.458*** (0.062)	0.967*** (0.036)	0.510*** (0.036)
	Adjusted R^2 (%)	23.088	72.892	41.520
	Number of observations	1,113	1,113	1,113
Positive extreme events	α (%)	0.067 (0.058)	0.110** (0.055)	0.043 (0.046)
	β	−0.599*** (0.045)	0.419*** (0.030)	1.016*** (0.041)
	Adjusted R^2 (%)	25.983	20.549	71.340
	Number of observations	1,113	1,113	1,113

*Note: standard errors according to Arellano (1987) are in brackets. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.*

Table 5 shows the results of the CAPM model estimates. The parameters were determined by Pooled OLS estimation. The Jensen alpha indicators and the corresponding standard errors are presented in the table in percentages. The explanatory power of the models is also provided in percentages. It is clear from the table that when all extreme events are considered, the contrarian strategy provides significant positive excess return. The Jensen alpha is 12.2 basis points (annualised[2]: 35.77 per cent) and is significant at a 5-per cent significance level. On average, the contrarian portfolio generates this much more excess return compared to the market portfolio in the examined event windows. *Piccoli et al.* (*2017*), examining all extreme events, estimate a daily excess return of 14 basis points in the US stock market. When examining the full sample, it can be shown for the loser portfolios that they outperform the market after extreme events. The Jensen alpha indicator is 13.4 basis points (annualised: 39.94 per cent) and is significant at a 1-per cent significance level. The explanatory power of the model is 52.79 per cent. When examining the full sample, no significant excess return can be identified for the

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[2] The annualised values are based on 251 trading days.

winner portfolios. This suggests that the excess returns of the contrarian strategy may be attributable to the loser portfolios' outperforming.

In the case of the subsample containing negative extreme events, the contrarian strategy also generates significant excess return. The Jensen alpha indicator is 15.7 basis points (annualised: 48.16 per cent) and is significant at a 5-per cent significance level. *Piccoli et al* (*2017*) estimate a daily excess return of 18 basis points for the negative subsample in the US stock market. The explanatory power of the model in this case is already 23.09 per cent. By contrast, in the case of the subsample containing positive events, the contrarian strategy generates no excess returns. This implies that this strategy is more likely to be successful in the case of negative extreme events.

Loser portfolios beat the market under both negative and positive events. For the subsample of positive events, the Jensen alpha indicator is 11 basis points (annualised: 31.71 per cent) and is significant at a 5-per cent significance level. On the other hand, for the subsample of negative events, the Jensen alpha indicator is 14.8 basis points (annualised: 44.78 per cent) and is significant at a 5-per cent significance level. After the extreme event, the loser portfolios beat the market in all cases over a horizon of 21 days.

In estimating the models, we assume that the market risk is known in advance, and thus the β indicators illustrate the ex-post market risk. In the models, the market risk of the contrarian strategy is obtained as the difference between the market risks of the loser and winner strategies. If β is positive and significant, it suggests the market risks of the loser portfolio exceeds that of the winner portfolio, while in the case of negative significant the market risk of the winner portfolio exceeds that of the loser portfolio. For the full sample the β of the loser portfolio is 0.77, while the market risk of the winner portfolio is 0.69. The market risk of the contrarian strategy is 0.08 and is not significant. This suggests that for the full sample the market risk of the loser and winner portfolios is not significantly different, i.e. the differences in returns are not attributable to the differences in market risks. In the case of the full sample, the very low explanatory power of the CAPM model is also attributable to the fact that the market risk of the contrarian strategy is not significantly different from zero. There is already significant positive difference in the subsample of negative events, but the positive significant Jensen alpha indicator estimated under the ex-post β suggests that the performance difference is not only attributable to the differences in the systematic risk of loser and winner portfolios. The work of *Piccoli et al.* (*2017*) and the results in *Table 4* also highlight the fact that the risk factors included in the popular asset pricing models (CAPM, FF3, Carhart, FF5) do not explain the difference between the performance of loser and winner portfolios. This implies that investors' overreaction to extreme events appears in the stock market as an explanatory factor for returns, independent of other systematic risk factors.

6. Robustness tests

Extreme events are not independent of each other, and several extreme events may appear in a single event window. The analysis of overlapping events may bias our results. In the case of a market correction, loser equities are those that suffer the largest fall, and from a market efficiency perspective based on the CAPM model, these equities are also more susceptible to market changes, i.e. they have higher market risk (β). When the examined event overlaps with an extreme event of opposite direction and the market returns, this opposite event will trigger stronger reaction of loser equities. Then, the excess return of the contrarian strategy cannot be attributed to the overreaction, but rather to differences in the market risk of winner and loser portfolios. This is why we present the results in *Table 5* on the subsample of the non-overlapping event windows under different extreme event definitions. The purpose of the various extreme event definitions is to control for the extreme event definitions that largely determine the strategy.

Table 6
Non-overlapping event windows according to different extreme event definitions

Samples	Parameters	Loser-Winner	Loser	Winner
Non-overlapping event windows (1 per cent, with 500 days)	α (%)	0.143* (0.084)	0.183** (0.078)	0.039 (0.048)
	β	−0.352*** (0.137)	0.421*** (0.079)	0.773*** (0.077)
	Adjusted R^2 (%)	2.981	7.589	25.608
	Number of observations	735	735	735
Non-overlapping event windows (5 per cent, with 500 days)	α (%)	−0.014 (0.066)	0.044 (0.056)	0.058 (0.039)
	β	−0.060 (0.128)	0.564*** (0.084)	0.624*** (0.067)
	Adjusted R^2 (%)	−0.026	9.309	15.462
	Number of observations	1,071	1,071	1,071
Non-overlapping event windows (1 per cent, with 250 days)	α (%)	0.129* (0.074)	0.151** (0.069)	0.023 (0.043)
	β	−0.173 (0.132	0.486*** (0.075)	0.659*** (0.074)
	Adjusted R^2 (%)	0.873	12.619	27.178
	Number of observations	735	735	735
Non-overlapping event windows (5 per cent, with 250 days)	α (%)	0.067 (0.082)	0.115* (0.065)	0.048 (0.053)
	β	−0.187* (0.106)	0.513*** (0.071)	0.700*** (0.058)
	Adjusted R^2 (%)	0.551	6.932	20.068
	Number of observations	840	840	840

Note: standard errors according to Arellano (1987) are in brackets. ***p < 0.01, **p < 0.05, *p < 0.1.

Table 6 presents the results of the CAPM model estimations on subsample of non-overlapping event windows by different extreme event definitions. The parameters were determined by Pooled OLS estimation. The Jensen alpha indicators and the corresponding standard errors are presented in the table in percentages. The explanatory power of the models is also provided in percentages. When extreme events are identified using the original definition, the Jensen alpha indicator of the contrarian strategy is 14.3 basis points (annualised: 43.27 per cent) and is significant at a 10-per cent significance level. *Piccoli et al.* (*2017*) estimate a daily excess return of 13 basis points on a subsample of non-overlapping events, which in their case is significant at a 1-per cent level. The explanatory power of the model is 2.98, which suggests that less than 3 per cent of the variance of the difference between the loser and winner portfolio returns is explained by the differences in market risk. The market risk of the loser portfolio is significantly lower than the market risk of the winner portfolio, and thus the difference in returns is not attributable to the differences in market risk. The excess return on the loser portfolio is 18.3 basis points (annualised: 58.07 per cent) and is significant at a 5-per cent significance level. This implies that the excess return of the contrarian strategy comes from the excess return of the loser portfolio also in the case of non-overlapping events, and the excess return is not attributable to the differences in market risk. *Table 5* shows that in the case of different extreme events, investor's overreaction can be identified only for extreme events defined under a stricter, 1-per cent threshold. The performance of the contrarian strategy is clearly independent of the length of the time series selected for the purposes of defining extreme events; we can choose 250 or 500 trading days. This suggests that the performance of the contrarian strategy increases under tighter extreme thresholds.

Table 7 shows the results of additional robustness tests. The parameters of the CAPM model were determined by Pooled OLS estimation. The Jensen alpha indicators and the corresponding standard errors are presented in the table in percentages. The explanatory power of the models is also provided in percentages. In the first case, we examined the subsample of event windows with short-term reversal. We selected the event windows so that the event window contained another extreme event of opposite direction. On this subsample, the Jensen alpha indicator of the contrarian strategy is 24.9 basis points (annualised: 86.65 per cent) and is significant at a 1-per cent significance level. *Piccoli et al.* (*2017*) identified an excess return of 19 basis points in the case of event windows with short-term reversal. The market risk of loser and winner portfolios does not differ significantly. The excess return of the contrarian strategy is attributable to the excess return on the loser portfolio. It is obvious here as well that the excess return is not attributable to the differences in market risk.

In the second case, we examined the subsample of momentum event windows. We selected the event windows so that they contained another extreme event of the same direction. In this case, we identified no significant excess returns. The market risk of loser portfolios is significantly higher than that of the winner portfolios. In the case of the momentum event windows, the contrarian strategy generates no profit.

Table 7

Robustness tests

Samples	Parameters	Loser-Winner	Loser	Winner
Event windows with short-term reversal	α (%)	0.249*** (0.079)	0.183** (0.073)	−0.066 (0.049)
	β	−0.048 (0.136)	0.701*** (0.053)	0.749*** (0.090)
	Adjusted R^2 (%)	0.122	57.162	58.208
	Number of observations	672	672	672
Momentum event windows	α (%)	0.035 (0.04)	0.092 (0.089)	0.057 (0.073)
	β	0.221** (0.106)	0.860*** (0.059)	0.639*** (0.054)
	Adjusted R^2 (%)	5.763	64.825	57.507
	Number of observations	777	777	777
Event windows with multiple extreme events	α (%)	0.265*** (0.088)	0.244*** (0.081)	−0.020 (0.066)
	β	0.137 (0.098)	0.820*** (0.049)	0.683*** (0.055)
	Adjusted R^2 (%)	2.600	68.320	61.531
	Number of observations	903	903	903
Event windows of high-volatility periods	α (%)	0.157* (0.081)	0.146** (0.074)	−0.011 (0.057)
	β	0.078 (0.104)	0.791*** (0.052)	0.712*** (0.058)
	Adjusted R^2 (%)	0.645	62.249	58.937
	Number of observations	1,113	1,113	1,113
Event windows of low-volatility periods	α (%)	0.087 (0.061)	0.120** (0.052)	0.033 (0.035)
	β	0.095 (0.119)	0.716*** (0.078)	0.621*** (0.059)
	Adjusted R^2 (%)	0.407	33.827	35.262
	Number of observations	1,113	1,113	1,113

*Note: standard errors according to Arellano (1987) are in brackets. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.*

In the third case we examined event windows with multiple extreme events. We selected the event windows such that there was an overlap of more than 1 extreme events in the event window regardless of the direction of the events. On this subsample, the Jensen alpha indicator of the contrarian strategy is 26.5 basis points (annualised: 94.07 per cent) and is significant at a 1-per cent significance level. *Piccoli et al.* (*2017*) identified an excess return of 23 basis points in the case of event windows with multiple extreme events. The market risk of loser and winner portfolios does not differ significantly.

In the fourth and fifth cases, the event windows were grouped based on the volatility of market portfolio prior to the extreme event. Based on the work of *Piccoli et al.* (*2017*), volatility was measured by the standard deviation of the returns on the market portfolio over 126 trading days preceding the extreme event. The median of the measured standard deviations was used as a breakpoint. On the sample of event windows of high volatility, the excess return of the contrarian strategy is 15.7 basis points (annualised: 44.27 per cent) and is significant at a 10-per cent significance level. On the sample of low volatility event windows the excess return of the contrarian strategy is not significant. No significant differences can be observed in market risks in either case.

Based on the robustness tests, we can state that contrarian strategy performs better in the case of event windows with short-term reversal than in the event windows with extreme events of the same direction. The clustering of high market volatility and extreme events is also beneficial to the performance of the contrarian strategy.

7. Conclusions

This paper examined investors' reactions to extreme events in the Hungarian stock market. The literature has already demonstrated many times that investors' overreaction can be observed in the stock market of both the United States and Hungary. Moreover, *Piccoli et al.* (*2017*) observed this phenomenon in the US stock market after extreme events as well. Based on this methodology, we investigated investors' reactions after extreme events in the Hungarian stock market with a view to contributing to the existing Hungarian literature analysing investors' reactions.

The research showed that after extreme events loser equities significantly outperform winner equities, and thus investors' overreaction to extreme events can be observed. These reactions are in line with the reactions presented by *Piccoli et al.* (*2017*), but it is also clear that these reactions are less pronounced for Hungarian equities than in the US stock market. Negative abnormal returns in the case of winners can be observed on the first 6 days after the event. The average cumulative abnormal returns of the contrarian strategy increases significantly in the first 4 days after the extreme event, when we observe a cumulative abnormal value of 2.02 per

cent. Based on the analysis of the average cumulative abnormal returns, investors' overreaction can be confirmed.

After examining investors' reactions, we highlighted the fact that – due to the outperformance of the loser portfolios – application of the contrarian strategy after extreme events generates profit for investors. By purchasing loser portfolios and short selling winner portfolios we followed a contrarian strategy, and showed that these portfolios outperform the market portfolio over a 21-day trading horizon, particularly in the case of negative events. The excess return of the contrarian strategy is shaped by the excess return on loser portfolios, since these portfolios always beat the market on a horizon of 21 days. Furthermore, the significant positive Jensen alpha indicators suggest that the excess return of the contrarian strategy is not attributable to the differences in the market risk of loser and winner portfolios, which implies that investors' overreaction to extreme events appears in the stock markets as a factor explaining returns, independent of systematic risk factors. Thus, the loser portfolios' outperforming reflects investors' overreaction rather than differences in market risk.

The robustness tests showed that the performance of the contrarian strategy can be identified under tighter extreme value thresholds. The clustering of the event windows with short-term reversal, high market volatility and extreme events is beneficial to the performance of the contrarian strategy. This suggests that overreaction and market volatility are not independent of each other. We can conclude from the results that buying loser equities or developing a contrarian strategy after extreme events may generate profit for investors in the short run in the Hungarian stock market.

References

Alonso, A. – Rubio, G. (1990): *Overreaction in the Spanish equity market*. Journal of Banking and Finance, 14(2–3): 469–481. https://doi.org/10.1016/0378-4266(90)90060-f

Andor, Gy. – Ormos, M. – Szabó, B. (1999): *Return Predictability in the Hungarian Capital Market*. Periodica Polytechnica Social and Management Sciences, 7(1): 29–45.

Arellano, M. (1987): *Computing Robust Standard Errors for Within-groups Estimators*. Oxford Bulletin of Economics and Statistics, 49(4): 431–434. https://doi.org/10.1111/j.1468-0084.1987.mp49004006.x

Baltussen, G. – Swinkels, L. – van Vliet, P. (2019): *Global Factor Premiums*. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.3325720

Banz, R.W. (1981): *The relationship between return and market value of common stocks*. Journal of Financial Economics, 9(1): 3–18. https://doi.org/10.1016/0304-405X(81)90018-0

Brooks, C. – Persand, G. (2001): *Seasonality in Southeast Asian stock markets: some new evidence on day-of-the-week effects*. Applied Economics Letters, Vol. 8, pp. 199–213. https://doi.org/10.1080/13504850150504504

Brooks, R.M. – Patel, A. – Su, T. (2003): *How the Equity Market Responds to Unanticipated Events*. The Journal of Business, 76(1): 109–133. https://doi.org/10.1086/344115

Brown, C.K. – Harlow, W.V. (1988): *Market overreaction: Magnitude and intensity*. The Journal of Portfolio Management, 14(2): 6–13. https://doi.org/10.3905/jpm.1988.409137

Brown, C.K. – Harlow, W.V. – Tinic, M.S. (1988): *Risk aversion, uncertain information, and market efficiency*. Journal of Financial Economics, 22(2): 355–385. https://doi.org/10.1016/0304-405X(88)90075-X

Chan, K.C. (1988): *On the Contrarian Investment Strategy*. The Journal of Business, 61(2): 147–163. https://doi.org/10.1086/296425

Chan, W.S. (2003): *Stock price reaction to new and no-news: drift and reversal after headlines*. Journal of Financial Economics, 70(2): 223–260. https://doi.org/10.1016/s0304-405x(03)00146-6

Coleman, L. (2012): *Testing equity market efficiency around terrorist attacks*. Applied Economics, 44(31): 4087–4099. https://doi.org/10.1080/00036846.2011.587778

Corrado, C. – Jordan, B.D. (1997): *Risk Aversion, Uncertain Information, and Market Efficiency.* Review of Quantitative Finance and Accounting, 8: 51–68. https://doi.org/10.1023/a:1008292620583

Csillag, B. – Neszveda, G. (2020): *A gazdasági várakozások hatása a tőzsdei momentumstratégiára (Impact of economic expectations on the momentum strategy)*. Közgazdasági Szemle (Economic Review), 67(November): 1093–1111. http://doi.org/10.18414/KSZ.2020.11.1093

Daniel, K.D. – Hirshleifer, D.A. – Subrahmanyam, A. (1997): *A Theory of Overconfidence, Self-Attribution, and Security Market Under- and Over-reactions*. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.2017

De Bondt, W.F.M. – Thaler, H.R. (1985): *Does the Stock Market Overreact?* Journal of Finance, 40(3): 793–805. https://doi.org/10.1111/j.1540-6261.1985.tb05004.x

De Bondt, W.F.M. – Thaler, H.R. (1987): *Further Evidence on Investor Overreaction and Stock Market Seasonality*. Journal of Finance, 42(3): 557–581. https://doi.org/10.1111/j.1540-6261.1987.tb04569.x

Deev, O. – Kajurová, V. – Stavarek, D. (2019): *Stock market speculative bubbles: the case of Visegrad countries*. Proceedings of 30th International Conference Mathematical Methods in Economics, pp. 107–111. https://is.muni.cz/do/econ/soubory/aktivity/mues/35953888/019_Deev.pdf

Fama, E.F. (1970): *Efficient Capital Markets. A Review of Theory and Empirical Work*. Journal of Finance, 25(2): 383–417. https://doi.org/10.1111/j.1540-6261.1970.tb00518.x

Fama, E.F. (1998): *Market Efficiency, Long-Term Returns, and Behavioral Finance*. Journal of Financial Economics, 49(3): 283–306. https://doi.org/10.2139/ssrn.15108

Grubits, L. (1995a): *A hatékony tőkepiacok elmélete és a Pick-részvény árfolyama I (Efficient Market Hypothesis and Pick equity price I).* Bankszemle, 39(3–4): 42–53.

Grubits, L. (1995b): *A hatékony tőkepiacok elmélete és a Pick-részvény árfolyama II (Efficient Market Hypothesis and Pick equity price II)*. Bankszemle, 39(5): 21–28.

Hart, J., van der – Slagter, J.E. – van Dijk, D. (2003): *Stock selection strategies in emerging markets*. Journal of Empirical Finance, 10(1–2): 105–132. https://doi.org/10.1016/S0927-5398(02)00022-1

Himmelmann, A. – Schiereck, D. – Simpson, M.W. – Zschoche, M. (2012): *Long-term reactions to large stock price declines and increases in the European stock market: a note on market efficiency*. Journal of Economics and Finance, 36(2): 400–423. https://doi.org/10.1007/s12197-010-9125-z

Hudson, R. – Atanasova, C.V. (2008): *Short Term Overreaction, Underreaction and Momentum in Equity Markets*. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.1157927

Ising, J. – Schiereck, D. – Simpson, M.W. – Thomas, T.W. (2006): *Stock returns following large 1-month declines and jumps: Evidence of overoptimism in the German market*. The Quarterly Review of Economics and Finance, 46(4): 598–619. https://doi.org/10.1016/j.qref.2006.02.005

Jegadeesh, N. – Titman, S. (1993): *Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency*. The Journal of Finance, 48(1): 65–91. https://doi.org/10.1111/j.1540-6261.1993.tb04702.x

Kahneman, D. – Tversky, A. (1979): *Prospect Theory: An Analysis of Decision under Risk*. Econometrica, 47(2): 263–292. https://doi.org/10.2307/1914185

Lakatos, M. (2016): *A befektetői túlreagálás empirikus vizsgálata a Budapesti Értéktőzsdén (Empirical analysis of investors' overreaction on the Budapest Stock exchange)*. Közgazdasági Szemle (Economic Review), 43(4): 762–786. https://doi.org/10.18414/KSZ.2016.7-8.762

Lukács, P. (2003): *Értékpapírok hozamának eloszlása és a tőzsdei kapitalizáció (Stock Return Distribution and Market Capitalisation)*. Szigma, 34(1–2): 31–43.

Mérő, B. – Nagy, O. – Neszveda, G. (2019): *Új faktorok tesztelése az empirikus eszközárazásban (Testing of new factors in empirical asset pricing)*. Szigma, 50(4): 263–281.

Molnár, M.A. (2006): *A Budapesti Értéktőzsde hatékonysága (Efficiency of the Budapest Stock Exchange)*. Hitelintézeti Szemle, 5(5–6): 28–35. http://epa.oszk.hu/02700/02722/00025/pdf/EPA02722_hitelintezeti_szemle_2006_5-6_28-35.pdf

Nagy, B. – Ulbert, J. (2007): *Tőkepiaci anomáliák (Capital market anomalies)*. Statisztikai Szemle (Statistical Review), 85(12): 1014–1032.

Pham, V.T.L. – Nguyen, D.Q.T. – Tô, T.-D. (2008): *Chapter 10 Abnormal returns after large stock price changes: Evidence from Asia-Pacific markets*. In: Kim, S-J. – Mckenzie, M.D. (ed.): Asia-Pacific Financial Markets: Integration, Innovation and Challenges, pp. 205–227. https://doi.org/10.1016/S1569-3767(07)00010-6

Piccoli, P. – Chaudhury, M. – Souza, A. – da Silva, W.V. (2017): *Stock overreaction to extreme market events*. North American Journal of Economics and Finance, 41(July): 97–111. https://doi.org/10.1016/j.najef.2017.04.002

Rappai, G. (1995): *A hatékony tőkepiacok elmélete a gyakorlatban (Efficient Market Hypothesis in practice)*. Published in: Studio Oeconomica jubilee volume of essays and studies, Janus Pannonius Tudományegyetem, Közgazdaságtudományi Kar, Pécs.

Shiller, R. (1981): *Do Stock Prices Move Too Much to be Justified by Subsequent Changes in Dividends?* American Economic Review, 71(3): 421–436.

Yuan, Y. (2015): *Market-Wide Attention, Trading, and Stock Returns.* Journal of Financial Economics, 116(3): 548–564. https://doi.org/10.2139/ssrn.1105532

Zarowin, P. (1990): *Size, Seasonality, and Stock Market Overreaction*. Journal of Financial and Quantitative Analysis, 25(1): 113–125. https://doi.org/10.2307/2330891