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Market Timing Investment Methods on the Budapest Stock Exchange*

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A large body of literature confirms that simple investment methods based on timing can outperform and thus be an alternative to traditional investment strategies. The study tests this hypothesis on the Budapest Stock Exchange stock index: a simple timing strategy using 4,619 moving averages was tested on 554,935 trades over the period from 1998 to 2022. The study finds that a wide range of the 4,619 variants performed well on in-sample data, but most could not achieve outperformance out of sample. In some cases, overfitting cannot be ruled out, nor can the effect of randomness due to the low number of cases. The robust variant selected on the in-sample data outperforms out of sample and over the full period at trading costs. However, at a one per cent significance level the Monte Carlo simulation of this variant does not allow the null hypothesis to be rejected, i.e. it cannot be ruled out that randomness or market noise caused the results.

Journal of Economic Literature (JEL) codes: G17, C15, C41

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1. Introduction

Research in the literature has examined a number of timing strategies over the past decades, with the primary aim of providing a solution to the problem of the stock market risk premium. In other words, although the stock market risk premium is positive across a wide range of stock markets, a number of past observations suggest that the premium can be negative even over a long period of time. For example, the Irish stock market had a risk premium of –0.6 per cent between 1900 and 1939, the Swiss stock market –0.5 per cent between 1910 and 1949, and the German stock market –1.8 per cent between 1960 and 1979 (*McQuarrie 2021*). In addition to the above, it can be observed that not only the risk premium, but

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also the real return can be negative even for long-term investments. Data from *Anarkulova et al.* (*2022*) suggest that the probability of a negative real return is significant (12–15 per cent) over a 20–30 year time horizon for a broadly diversified equity portfolio (stock market index), and calculations by *Bihary et al.* (*2018*) suggest that the risk of holding equities increases for 30 years, and only then starts to decrease, reaching zero at 100 years. The modern portfolio theory of *Markowitz* (*1952*) provides a traditional solution to these risks, while non-traditional solutions include market timing methods.

Many market timing solutions are linked to technical analysis signals, including moving average signals. The work of *Brock et al.* (*1992*), who laid the foundations for the study of moving averages and other trading rules, is noteworthy in this respect. In their research, they showed the predictive ability of the 1-day and 50-day, 1-day and 150-day, and 1-day and 200-day moving averages on the Dow Jones Industrial Average index for the period 1897–1986. In the 30 years since the original research, several more studies have continued to test moving averages using a similar methodology on a wide range of stocks, stock market indices and investment instruments. Despite the number of analyses, no clear conclusions can be drawn from the material. In some cases, the authors did not conduct out-of-sample tests, while in other cases the role of costs was not taken into account, and there are several papers that failed to demonstrate the forecasting power of moving averages, i.e. that moving average strategy cannot be used to achieve outperformance.

This paper aims to test the hypothesis that market timing methods are alternatives to the traditional "buy-and-hold" strategies that follow from efficient markets theory and Markowitz's modern portfolio theory. A further aim of the study is to complement the above literature by using data from the BUX index to analyse moving average based crossover signals, building on the original methodology developed by Brock et al. but extending it to a wider range of moving averages, comprising 4,619 combinations, for a total of 554,935 trades. For this purpose, the data set for the last 25 years of the BUX index was used, separating the data set into in-sample (7 January 1998 to 29 December 2017) and out-of-sample (2 January 2018 to 30 December 2022) ranges. As far as the author knows, no comprehensive study using the BUX index has been performed to date.

To evaluate the results, the two best variants were selected according to pre-defined rules on the in-sample data, and the out-of-sample performance of these variants was also examined. Separation of the data into in-sample and out-of-sample stages and the pre-defined selection rules was necessary because without them, the variant trained on the historical data would be automatically selected, given that the large number of combinations requires that one of the variants should fit the historical data well with a high return. However, this does not mean that the model can be used to obtain optimal results on future data (out of sample). The results show that the model variant with the highest risk-adjusted return selected on the in-sample data ([31–5]) failed to outperform the BUX index on the out-of-sample data. However, the variant selected on the basis of the robustness criterion ([110–7]) was able to outperform out of sample on the in-sample data. The role of costs is also well outlined by the results, because if we ignore costs, the outperformance of the two selected model variants ([31–5] and [110–7]) is significant. Due to the low number of cases and the limited sample, a Monte Carlo simulation of the [110–7] variant was also performed. Based on the results, the null hypothesis cannot be rejected, i.e. the possibility that the outperformance is due to randomness cannot be excluded.

Based on the tests over the whole period, 45 per cent of the 4,619 variants outperformed if trading costs were not taken into account. Taking into account trading costs, only 9 per cent was able to outperform. This shows that moving averages also have some predictive ability for the BUX index, but the models are extremely sensitive to trading costs. However, this calls into question whether the methods can be put into practice, and it cannot be said that in reality they are useful, applicable alternatives to traditional strategies on the BUX index of the Budapest Stock Exchange.

The paper is structured as follows: *Section 2* reviews the literature, *Section 3* presents the methodology, and *Sections 4–6* provide an evaluation of the results.

2. Review of literature

Technical analysis is the collective name for methods of price forecasting that produce their predictions for the future from statistical tests based on past stock prices and trading volumes. By contrast, the efficient markets theory holds that stock prices reflect all past information, so that the past prices cannot be used to make predictions about the future (*Fama 1970; Malkiel 2003*). However, it is now largely proven that capital markets do not always meet the information efficiency condition of the efficient markets theory (*Komáromi 2002*). In addition, there are now hundreds of anomalies that generate excess return that contradict the theory of efficient markets (*Hou et al. 2018*), although many of these are economically insignificant and undetectable out of sample (*Falck et al. 2021*).

Among the hundreds of stock market anomalies, however, we find so-called price effects specifically related to the relationship between past price and future price. First, it was *De Bondt and Thaler* (*1985*) who showed that portfolios of past losers outperform portfolios of past winners. This long-term reversal effect was observed in the work of De Bondt and Thaler in the five years following portfolio compilation and is not the only anomaly in the relationship between past price and future price. In fact, reversal effects similar to those described above have been demonstrated not only over a long time scale, but also over a very short time scale of 1–4 weeks (*Jegadeesh 1990*). Moreover, in addition to the reversal effects observed in the short and long run, the momentum effect confirms that a link between past price and future price can be established (*Jegadeesh – Titman 1993*). In the case of the momentum effect, we find that portfolios of past winners (1–18 months) also outperform in the future (1–18 months). Thus, while reversal price effects can be identified in the very short (1–4 weeks) and very long (36–48 months) time horizons, in the medium term (1–18 months) the momentum effect can be observed across a wide range of stocks. The momentum effect can be observed even three decades after its discovery, even in intraday data (*Gao et al. 2023*), and is also present in manually collected stock market data from 1866 to 1907 (*Chabot et al. 2009*).

For the Budapest Stock Exchange, *Nagy and Ulbert* (*2007*) demonstrated the momentum effect and the long-term reversal effect for the period 1996–2007. A decade later, *Lakatos* (*2016*) observed that the long-term reversal phenomenon is still present on the Budapest Stock Exchange, i.e. past losers outperform past winners in the future. The momentum effect was identified in research conducted by *Mérő et al.* (*2019*) on the domestic stock market. Their study shows that momentum can be a statistically significant predictor of future return in the Hungarian stock market as well. Hungarian studies are also available on short-term reversal effects. *Neszveda – Vágó* (*2021*) investigated hypothetical trading strategies that are based on buying stocks that lose in the short term and selling stocks that win. The strategy also produced significantly positive returns on the Hungarian stock market over the period 1990–2019.

Responding to criticisms of the efficient market theory, *Malkiel* (*2003*) also addresses the above price effects in his paper. Among his findings is that most of the anomalies detected are not robust, are highly sample dependent, and are often the result of data mining. On the other hand, even if these correlations exist, they disappear once they are known, as we have seen in past cases. *Komáromi* (*2002*) summarises the problems with the anomalies identified by saying that although free lunches exist in capital markets, it is impossible to predict when, where and to what extent an investor can expect a free lunch.

In addition to price effects, studies are also available in the context of technical analysis signals. *Neely et al.* (*2011*) used simple moving averages, price momentum and trading volume data to predict the risk premium in the stock market. The predictive power of the examined signals had higher in- and out-of-sample explanatory power than the predictive power of macroeconomic factors examined by *Welch and Goyal* (*2008*).

Among the studies of simple trading rules, the work of *Brock et al.* (*1992)* can be considered as a starting point, given that they were the first to standardise the signals of the most popular technical instruments. Their tests involved simple trading rules based on timing, such as crossover signals of moving averages and breaking price levels. In their study on simple moving averages, they examined the crossover signals of the moving averages of 1 and 50 days, 1 and 150 days, and 1 and 200 days on the Dow Jones Industrial Average index over the period 1897–1986 in sample. Their findings include that rules based on technical analysis signals have predictive power, but that the ability to exploit this potential is severely limited by trading costs. The methodology laid down by Brock et al. has been confirmed by a number of subsequent studies in other markets over other time horizons. For example, *Bessembinder and Chan* (*1995*) showed excess returns on stock markets in Hong Kong, Japan, Korea, Malaysia, Thailand and Taiwan over the period 1975–1991 using Brock's rules. *Hudson et al.* (*1996*) were able to observe outperformance on the FT30 stock market index from 1935–1994, *Mills* (*1997*) on the FT30 index (1975–1994), and *Bessembinder and Chan* (*1998)* on the Dow Jones stock market index (1926–1991). Among the studies on stock markets in the region, *Kresta and Franek* (*2015*) found that 6-day and 27-day simple moving averages on the Czech stock index outperformed the stock index on 1993–2015 data, but the study was conducted only in sample. However, *Fang et al.* (*2012*) reviewed Brock's original rules over the period 1987–2011 (out of sample) and found that the out-of-sample performance of simple technical rules is extremely low. According to the authors, the unfavourable results are not due to the fact that market efficiency was higher during the period under study, but rather to the fact that the previous research overfit the signals on the in-sample data.

Technical analysis tools primarily generate their buy and sell signals based on the trading price and, in the case of some models, the trading volume. The models can be broadly grouped into four categories, of which moving averages are primarily a possible means of implementing trend-following behaviour. Other models include oscillator-type indicators (e.g. the Relative Strength Index), volatility indicators (e.g. Bollinger Bands) and indicators based on volume (*Marek – Šedivá 2017; Williams 2006*). Although a large number of trend-following models are available, most of them are based on moving averages, the crossover of moving averages, and the distance between them. Furthermore, it can be concluded that moving averages are closely related to the practical application of the momentum effect (*Marshall et al. 2010*). Research on moving averages is ongoing. *Avramov et al.* (*2021*) showed a 9 per cent annual abnormal return on the US stock market based on the distance of short-term (21-day) and long-term (200-day) moving averages in a cross-sectional analysis. The reported return exceeds the abnormal return from momentum, profitability premium and other anomalies. The results of the above study were confirmed by *Abudy et al.* (*2023*) in international stock markets with a cross-sectional analysis based on the distance between the 30-day and 300-day moving averages. In the context of technical analysis and price effects, a number of studies have addressed the role of market efficiency, i.e. the outperformance of strategies in markets, products and periods where market efficiency is low or declining. *Marshall et al.* (*2009*) have shown that the effectiveness of the rules defined by Brock is higher in low market capitalisation, low liquidity stock markets. *Li et al.* (*2023*) examined the results of strategies based on moving averages over different time periods in 40 stock markets. In addition to finding outperforming models in many stock markets, they found that signals are more efficient in stock markets in non-OECD countries, in stock markets in countries with low GDP and in capital markets with no long-term history of stock trading. Studies on the market efficiency of the Budapest Stock Exchange suggest that the stock market has some of the characteristics of capital markets in developing countries and some signs of market inefficiency (*Birău 2015; Molnár 2006*). Related to market efficiency, *Fernández et al.* (*2023*) found in the context of predicting the risk premium of the stock market that the predictive ability of the instruments studied by *Neely et al.* (*2011*) is higher under calm market conditions.

The role of cognitive biases in investor decisions also arises in relation to market timing, such as the momentum effect or some technical analysis tools. Among other things, the disposition effect can also be associated with certain market anomalies (e.g. momentum), and studies by *Joó and Ormos* (*2011*) suggest that the decisions of Hungarian stock market investors are also influenced by the disposition effect. For the domestic equity market, *Csillag and Neszveda* (*2020*) showed that investors' expectations affect the outcome of momentum strategies, so that the explanatory power of the momentum factor was significant in a period of positive consumer sentiment, but failed to significantly predict expected returns in the following period in times of negative consumer sentiment.

In addition to investor sentiment, the literature also highlights the importance of media attention (*Csillag et al. 2022*), different investor reactions to extreme events (*Rádóczy – Tóth-Pajor 2021*) and seasonality (*Neszveda – Simon 2022*) in the context of the momentum effect. Considering that the root of the price effect behind the moving averages and the momentum are the same, one might suspect that the above factors also influence the results of the moving average models used for timing. Based on *Csiki and Kiss* (*2018*), it is likely that during periods of regional shocks, the correlation between developed and regional markets is higher, and that these processes also affect the BUX index under study.

Overall, therefore, the available studies are contradictory, and there is a wide range of literature supporting and contradicting technical analysis and price effects. However, it is also observed that different circumstances can be defined under which the reliability of the signals is higher. These circumstances are often associated with market efficiency, cognitive biases by investors, market sentiment and increased media attention. From the literature review it can be seen that the moving average is a key element in models using market timing. Intensive research into the subject is still ongoing. They also have the advantage of being cost-effective to use, easy to implement and have a transparent operational structure, which is a significant advantage over the "black box" nature of machine learning-based models (*Buczynski et al. 2021*). The literature also shows that there are differences in market efficiency between capital markets in developed and developing countries. At the same time, market timing models show different results depending on market efficiency. Considering the market inefficiency observed on the Budapest Stock Exchange, this study can complement the international literature on moving average timing, which focuses largely on developed capital markets. The aim of this study is to complement the above literature by examining the moving averages of the BUX index, a popular tool of technical analysis, on the Budapest Stock Exchange.

3. Methodology

Following the methodology of *Brock et al* (*1992*), simple moving average crossover signals were used as the basis for the analysis. Although only a few combinations of moving averages were used in the original study, current computational capacity allows for in-sample and out-of-sample analyses extended to a wide range of variants (4,619 variants in total, 554,935 transactions).

The moving average crossing signal is based on the crossing of a short-period and a long-period simple moving average. The value of simple moving averages can be calculated from the arithmetic averages of the closing prices over period *t* as follows,

$$MA_t = \frac{\sum_{i=1}^{n} P_{t-i+1}}{n}, \tag{1}$$

where:

- P_t the closing price *t* date,
- MA_t is the simple moving average at time *t*,
- *n* is the number of days, the time period of the moving average.

Moving averages allow time-series analysis to find recurring patterns, trends and seasonality changes in the data set. Although a number of cross-sectional data sets have been investigated in the context of moving averages, following Brock's methodology, this study uses a time-series model.

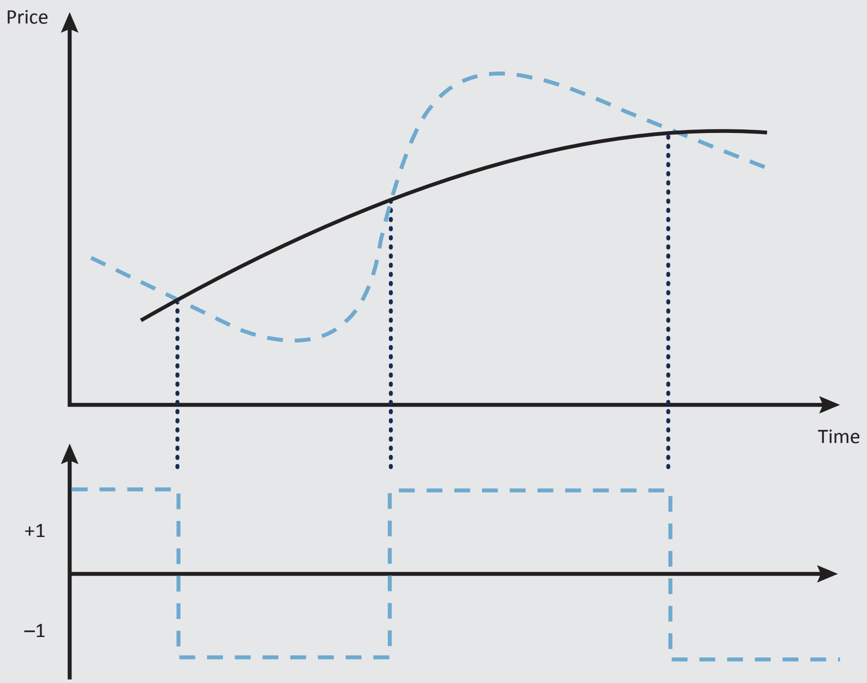
The buy and sell signals of the model can be linked to the crossover signals of two moving averages, where *f* is a short-term and *s* is a long-term moving average, as follows:

$$Buy \text{ if } MA(f)_{t>}MA\ (s)_t, \text{ and } MA(f)_{t-1} \leq MA(s)_{t-1}, \tag{2}$$

$$Sell \text{ if } MA(f)_{t<}MA\ (s)_t, \text{ and } MA(f)_{t-1} \geq MA(s)_{t-1}. \tag{3}$$

Based on the above, if the shorter-period simple moving average (hereinafter short SMA) is above the longer-period simple moving average (hereinafter long SMA), a buy signal is given. We can talk about a sell signal when the short SMA falls below the long SMA. In addition to opening a long position, a buy signal also closes a short position opened in the previous cycle. In the same way, the closing of a long position is accompanied by the opening of a short position, i.e. an open position is followed throughout the investment horizon (*Figure 1*).

Figure 1
Signals of short SMA and long SMA and the binary outcomes of the rules



Note: In the upper part of the figure, the dashed curve indicates the short SMA and the solid curve the long SMA. The lower part of the figure shows an illustrative example of a buy and a sell signal, where the +1 value of the output signal indicates a long and the -1 value indicates a short position. The figure clearly shows that when the short SMA crosses the long SMA curve in an upward direction, a buy is entered into. In the same way, if the short SMA crosses the long SMA curve on the downside, the long position is closed and a sell, short position is opened.

For the calculation of the crossover signals, the closing prices were taken into account, but the transactions were opened at the next day's opening price, given that in reality it is no longer possible to conclude a transaction after the closing price has been established. The return on a long position can be calculated as follows:

$$R = \frac{(1-f)\times CP-(1+f)\times OP}{OP}, \tag{4}$$

where:

- f = transaction fee,
- CP = closing price of the transaction,
- OP = opening price of the transaction.

The calculation of the return on short positions is as follows:

$$R = \frac{(1-f)\times OP-(1+f)\times CP}{OP}. \tag{5}$$

The aggregate returns of the transactions, the balance of each model variant, are calculated according to the following formula:

$$X = X_0 \times \prod_{i=1}^{n}(1 + R_i), \tag{6}$$

where:

- X_0 is the initial balance, which is 1 for all model variants,
- R_i is the return realised on transaction *i.*

The starting balance was always one unit. The return over the whole period was expressed using the compound annual growth rate (CAGR) as follows.

$$CAGR = \left(\frac{X}{X_0}\right)^{\left(1/N\right)} - 1. \tag{7}$$

In addition to the return, the maximum drawdown on model variations was also calculated. The calculation is based on an examination of the post-peak profit drawdown on the balance of the model variant. On the balance curve, the declines after all profit peaks are calculated [based on *equation* (*8*)], and the largest of these declines gives the maximal drawdown. For example, if the balance of a model variant drops to 400 points after a balance value of 800 points, and then to 700 points after another balance value of 1,000 points, then the measured drop is 50 per cent in the former case and 30 per cent in the latter, so the maximal drawdown for the model variant is 50 per cent.

$$\text{DD} = \frac{maximum\ balance - minimum\ balance\ after\ maximum\ balance}{maximum\ balance} \tag{8}$$

Given the maximal drawdown, the model calculates the risk-adjusted return based on the Managed Account Reports Ratio (MAR):

$$\text{MAR} = \frac{CAGR}{MDD}. \tag{9}$$

In the testing, the return and risk data of all combinations of 1–20 day short SMA and 20–250 day long SMA, i.e. 4,619 combinations with 0.3 per cent opening and closing transaction fees, were examined. In order to avoid overfitting, an in-sample period was set aside for which parameter optimisation was done. Optimal variants were selected according to predefined rules and then tested on out-of-sample data. The separation of the data into in sample and out of sample and the pre-defined selection rules was necessary because without them, the variant trained on the historical data is automatically selected, given that the large number of combinations requires that one of the variants should fit the historical data well. However, this does not mean that the model can be used to obtain optimal results on future data (out of sample).

In the selection of the optimal models, two variants were distinguished. In the one case, we select the variant with the highest risk-adjusted return (based on MAR) on the in-sample data and use it on the out-of-sample data and then on the full sample. In the other case, the selection is based on robustness criteria. This latter case is based on the principle that a trading method is considered less sensitive (robust) to overfitting if a small change in parameters does not cause a significant change in the outcome. To determine this, it is necessary to display the in-sample results of all variants in a heat map format (*see Section 5, Figure 2*).

Despite the fact that the study is carried out on 25 years of data, the number of cases behind each model variant is limited to a few hundred transactions (2,323 variants less than 95 transactions), so it is not clear whether the result is due to randomness, market noise, or whether the selected model actually has predictive and outperforming ability. To clarify the above, a Monte Carlo simulation is carried out following the guidelines of *Aronson* (*2006*).

The Monte Carlo simulation of market timing strategies is based on the output signals of the model variables, which are the binary values +1, –1 assigned to each day in the full sample (about 6,000 days). In addition, it is essential that the prices are converted into a stationary time series, as this is the only way to ensure that a upward or downward trend in the sample does not distort the performance of the buy and sell transactions. The stationary time series can be generated by the following operation.

$$\mathrm{LOG}\left(\frac{\mathrm{CP_t}}{\mathrm{CP_{t-1}}}\right) - ALR, \tag{10}$$

where:

- CP_t = the closing price at the end of day t,
- CP_{t-1} = the closing price at the end of day $t-1$,
- ALR = average of the logarithm of the time series.

According to the above, the return of each day needs to be calculated, transformed into the logarithm of the return, and the average of the returns is subtracted from the return of each day to obtain the stationary time series, whose mean and sum are zero. The next step is to sum the stationary time series and the outcome of the best model variant, i.e. to calculate the average return of the model variant based on the stationary time series and the outcomes (+1 if in a long position, –1 if in a short position).

Once the average return of the best model variant has been calculated, the elements of the 6,000-day stationary time series are randomly mixed (without replacement) and the average return is calculated from the randomly mixed data. This process is repeated 10,000 times and the average return calculated on the original data series is compared with the result of 10,000 randomly generated average returns (*Table 1*).

Table 1
Example simulations

Output signal	**–1**	**+1**	**+1**	**–1**	
Random daily return 1	–0.1%	+0.3%	–0.5%	+0.5%	**Average return**
Result 1	+0.1%	+0.3%	–0.5%	–0.5%	**–0.15%**
Random daily return 2	+0.3%	–0.1%	–0.5%	+0.5%	**Average return**
Result 2	–0.3%	–0.1%	–0.5%	–0.5%	**–0.35%**

Note: The table shows examples of four output signals on two randomly generated data series.

The null hypothesis in this study is that the best model variant is due to randomness, i.e. market noise. The alternative hypothesis is that the best variant has predictive power, and that the outperformance is not due to randomness. The significance level was set at 1 per cent. The null hypothesis can be rejected if the best 100 out of 10,000 randomly generated variants are equal to or better than the best 100 variants of the selected model. Although a significance level of 5 per cent is used in a wide range of studies, unfortunately this leads to many false results. For example, *Harvey et al.* (*2016*) find that 158 of the 296 stock market factors examined can be considered to be false discovery. Considering that the timing methods under investigation can be put into practice, the author deems it justified to require a stricter-than-usual level of significance.

The hypothesis of the study is that investors benefit from a better risk-return profile than the traditional "buy-and-hold" strategy with simple timing strategies. This can be established in the manner described above, i.e. on in-sample data, the chosen model outperforms out of sample over the whole period, based on pre-defined selection rules, and the results are confirmed by the robustness test (Monte Carlo simulation).

4. The data used

For the analysis, I used the BUX index prices (opening and closing prices), which are available on the Budapest Stock Exchange (BSE).[1] The BUX index shows the average price change of the shares with the largest capitalisation and volume traded in the BSE's equity section. The basket of the index contains a variable number of shares, from a minimum of 12 to a maximum of 25. The index itself is not a tradable product, but the OTP BUX index-tracking fund (ISIN HU0000704960) and the BUX index futures index, whose primary maturity in December (BUX2412) traded at high volume, are available in the BSE product range. Given that the above investment products involve trading costs that are not included in the BUX index data, an opening and closing trading cost of 0.3 per cent was taken into account in the analysis.

The full sample covered the period from 7 January 1998 to 31 December 2022. Data prior to 1998 were excluded because detailed exchange rate data are not available for this period, only closing prices, which are not sufficient to optimise the models. The in-sample data covered the period from 7 January 1998 to 29 December 2017 and the out-of-sample data covered the period from 2 January 2018 to 30 December 2022.

The results of the models tested were compared with the performance of the BUX index. The compound annual growth rate (CAGR) was used to compare returns, while the maximal drawdown (MDD) and the Managed Account Reports Ratio (MAR) were used to measure risk. The return and risk data for the benchmark index are summarised in *Table 2*.

Table 2
Return and risk of the benchmark

Period	MDD (%)	CAGR (%)	MAR
1998–2022	68.6	6.9	0.10
1998–2017	68.6	8.2	0.12
2018–2022	36.2	2.1	0.06

Note: The first row of the table shows the return and risk indicators of the BUX index for the full period, the second row for in sample and the third row out of sample.

[1] Source of data: https://bse.hu/pages/data-download

5. Results of the study

The study calculated the results of 4,619 variants of simple moving average signals (554,935 transactions in total). I tested the short-term moving averages with 1–20-day and the long-term moving averages with 20–250-day parameters. The return on the benchmark index over the in-sample period was 8.2 per cent. Only 248 (5.3 per cent) of the 4,619 variants in sample were able to achieve this result. The top 10 model variants are associated with 28–31 long-term and 5–10 short-term moving averages (*Table 3*).

Table 3
In-sample results sorted by return

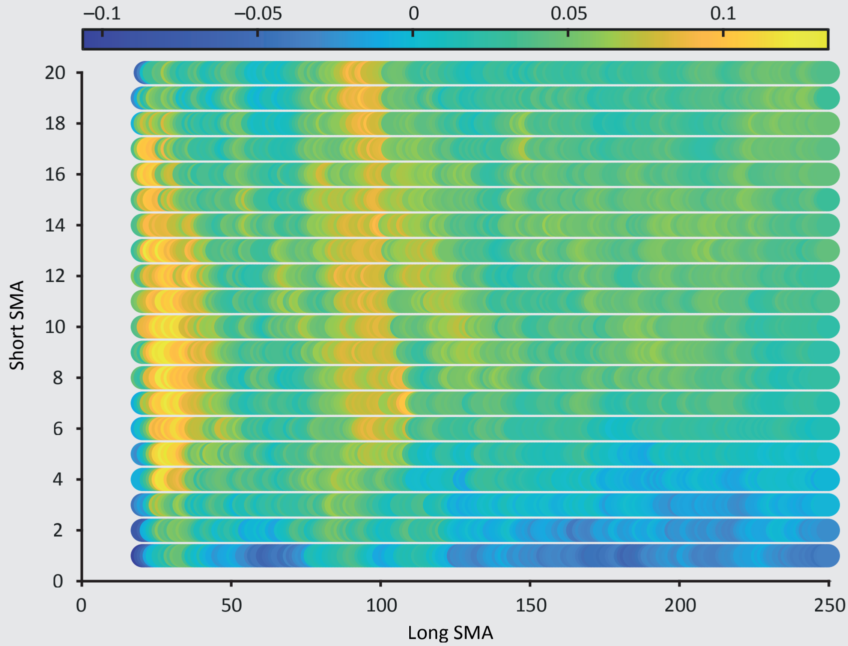
Long SMA	Short SMA	MDD (%)	CAGR (%)	MAR
31	5	–33.8	13.4	0.40
28	8	–38.7	12.4	0.32
31	8	–47.5	12.4	0.26
30	10	–50.6	12.4	0.24
31	7	–42.8	12.3	0.29
29	5	–30.6	12.3	0.40
29	8	–41.3	12.3	0.30
24	13	–54.4	12.2	0.22
28	13	–50.3	12.1	0.24
30	9	–42.9	12.0	0.28

Note: The long SMA and short SMA columns show the time period of the moving averages underlying the model variant. Under the MDD, the maximal drawdown, in the CAGR column the compound annual growth rate of the model variant, and in the MAR column the managed account reports ratio are shown.

The successful variants are clustered around two distinct areas. The first area is located in the range of crossover signals between the 25–35 day long-term and 5–11 day short-term moving averages (*Figure 2*).

The second, clearly distinguishable area is associated with the crossover signal of 90–110 long-term and 7–20 short-term moving averages. The in-sample results for these variants are summarised in *Table 4*.

Figure 2
Return (CAGR) of the 4,619 variations



Note: The figure shows the return (CAGR) for the 4,619 variants. Each point shows the results of one model variant tested over the period between 7 January 1998 and 29 December 2017. Yellow dots indicate high negative returns (CAGR) and blue dots indicate low negative returns (CAGR). The colour scale above the figure can help interpret the returns associated with the colour transitions.

Table 4
Returns on 90–110 long-term and 7–20 short-term moving averages

Long SMA	Short SMA	MDD (%)	CAGR (%)	MAR
110	7	–48.4	10.2	0.21
111	7	–52.8	10.2	0.19
96	19	–46.2	10.1	0.22
98	18	–51.3	9.8	0.19
101	14	–50.2	9.6	0.19
92	20	–43.2	9.4	0.22
109	7	–54.6	9.1	0.17
102	14	–50.9	9.0	0.18
88	12	–43.1	9.0	0.21
99	17	–53.9	9.0	0.17

Note: The long SMA and short SMA columns show the time period of the moving averages underlying the model variant. Under the MDD, the maximal drawdown, in the CAGR column the compound annual growth rate of the model variant, and in the MAR column the managed account reports ratios are indicated.

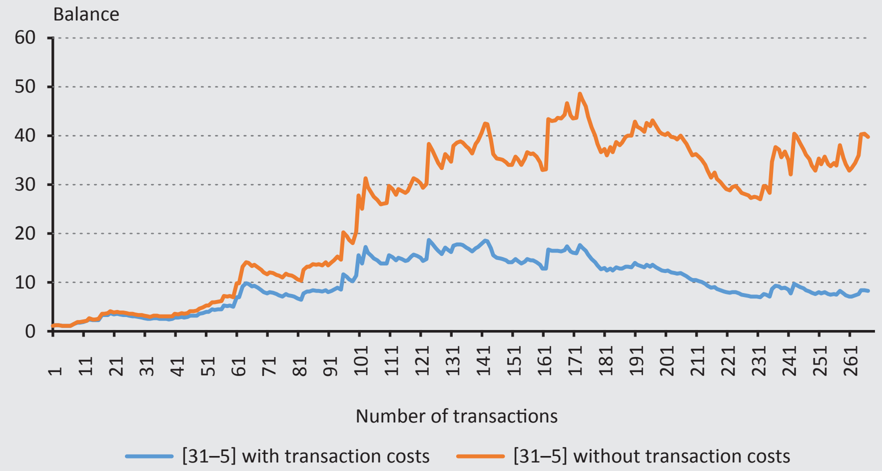
The in-sample data show that 5.3 per cent of the model variants have comparable results to the benchmark index. However, it cannot be stated with certainty that the results shown are not explained by overfitting, and thus the best models selected on in-sample data need to be tested on out-of-sample data as well.

To avoid overfitting and hindsight bias, a variant each was selected from the in-sample data based on the highest risk-adjusted return (MAR) and robustness. The criterion of the highest risk-adjusted return was met by the crossover signal of the 31-day long-term and 5-day short-term moving average, i.e. the [31–5] model variant. While this variant showed the best performance of all cases (both in terms of CAGR and MAR), the results can also be considered robust on the in-sample data, given that small changes in parameters did not cause significant variation in returns. For the second model selected, we can only speak about robustness. This is the area bounded by the 90–110 long-term and 7–20 short-term moving averages shown in *Figure 2*, where we see variants that are not the best in terms of outcome indicators (CAGR and MAR), but nevertheless outperform the benchmark index. In this area, we find close parameter variations with similar result indicators, i.e. the robustness criterion holds (small changes in parameters do not cause significant differences in the results). Here, the best performing model was the 110-day long-term and 7-day short-term moving average crossover signal ([110–7] model variant). No other area can be identified from the in-sample data that meets the criteria for highest risk-adjusted return or robustness. Based on the above selection criteria, the out-of-sample studies will continue with models [31–5] and [110–7].

The out-of-sample tests covered the period from 2 January 2018 to 30 December 2022. Over this period, the benchmark index returned 2.1 per cent (CAGR), with a maximal drawdown of 36.2 per cent. The [31–5] model variant underperformed the benchmark index with an out-of-sample result of –7.9 per cent compound annual growth rate, with a maximal drawdown of 44.7 per cent. The results of the [110–7] model variant were better, but this variant could not outperform in absolute returns (CAGR 2 per cent), only approaching the benchmark index returns (CAGR 2.1 per cent). At the same time, the return achieved with the benchmark index was achieved with almost half the risk (maximal drawdown of 16.5 per cent), so the MAR of 0.12 is twice the MAR of the benchmark index (0.06).

Thus, it is likely that the [31–5] variant provided an outperforming result on the in-sample data due to overfitting. This is also evident from the balance curve of the variety over the whole period after the 200th transaction (*Figure 3*). While our end-period balance with the benchmark index was 5.4 units with a starting balance of one unit, the end-period balance of the [31–5] variant was 39.8 units without costs and 8.1 units with costs. To summarise the results, the [31–5] variant outperforms in terms of CAGR and MAR both in sample and over the full period, regardless of trading costs, but not on out-of-sample data. The outperformance measured over the whole period is entirely due to the in-sample results.

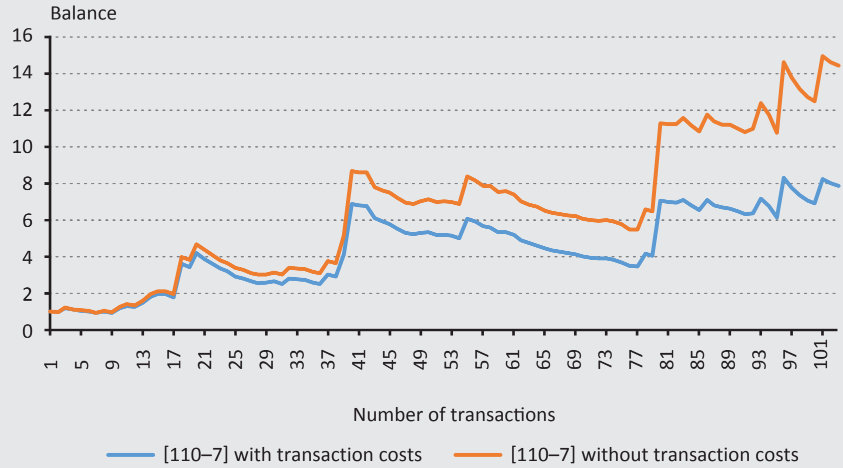
Figure 3
Changes in the balance of model variant [31–5]



Note: In the period between 7 January 1998 and 30 December 2022. The period before the 200th transaction covers the in-sample transactions.

For the [110–7] variant, a more stable balance change can be observed over the full sample (*Figure 4*). While our end-period balance with the benchmark index was 5.4 units with a starting balance of one unit, the end-period balance of the [110–7] variant was 14.4 units without costs and 7.9 units with costs. The [110–7] variant outperforms both in sample and over the whole period in terms of CAGR and MAR (even with trading costs), but only in terms of MAR for out-of-sample data. However, the low number of cases (103 transactions) in this variant makes it more likely that randomness, or market noise, caused the outperforming result.

Figure 4
Changes in the balance of model variant [110–7]



Note: In the period between 7 January 1998 and 30 December 2022. The period before the 82nd transaction covers the in-sample transactions.

Table 5 shows the full-period results of the two variants with and without trading costs. In the full sample, both model variants outperformed the benchmark index. Outperformance regarding out-of-sample data is only seen for variant [110–7], but due to the low number of cases, it is useful to perform a robustness test to assess the probability that the observed result is due to market noise or randomness. The role of costs is also well outlined based on the results, since if we ignore costs, the outperformance with the two model variants selected is significant. Over the full period, 45 per cent of all model variants outperform the benchmark index without costs, but only 9 per cent outperform when costs are taken into account. This observation rather suggests that moving averages have some predictive power, but that models are very sensitive to trading costs.

Table 5
Results measured over the full period

Period	MDD (%)	CAGR (%)	MAR
Benchmark index	68.6	6.94	0.10
[31–5] with costs	63.4	8.7	0.14
[31–5] without costs	44.6	15.9	0.36
[110–7] with costs	41.2	8.6	0.21
[110–7] without costs	21.3	11.3	0.53

Note: The MDD column of the table shows the maximal drawdown, the CAGR column the compound annual growth rate of the model variant, and the MAR column the return per unit of maximal drawdown.

The analysis detailed above differs from the original research by *Brock et al*. (*1992*) in terms of the trading direction. This was because it only included long positions and the authors ignored the short positions. With respect to the BUX index, when looking at the full sample and taking into account trading costs, the exclusion of short positions does not significantly improve the results of the models. Although there is a decrease in risk for the best performing variants (*Table 6*), the number of trades is significantly reduced when short positions are excluded, with only 30–40 for the best performing variants.

Table 6
Results over the full sample excluding short positions

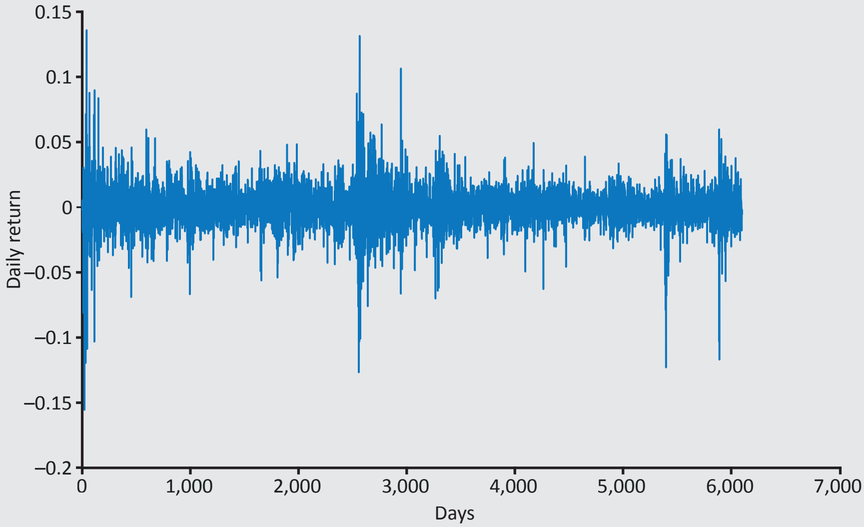
Long SMA	Short SMA	MDD (%)	CAGR (%)	MAR
105	14	17.7	9.3	0.53
96	19	16.9	8.7	0.52
109	14	18.6	9.4	0.5
101	14	18.5	9.2	0.5
103	15	18.4	9.1	0.5
Benchmark index		68.6	6.94	0.10

Note: The long SMA and short SMA columns show the time period of the moving averages underlying the model variant. Under the MDD, the maximal drawdown, in the CAGR column the compound annual growth rate of the model variant, and in the MAR column the managed account reports ratio per unit of maximum drawdown are indicated. For the above model variants, only signals related to the opening of buy transactions were taken into account.

6. Robustness test

Despite the fact that the BUX index data in the back-testing goes back 25 years, the number of transactions in each model variant is considered low (a few hundred). This certainly raises the possibility of market noise, and therefore a robustness test on the [110–7] variant is required, as described in *Section 3*. After converting the daily returns to a stationary time series (*Figure 5*), the binary outputs (–1, +1 values) of the [110–7] variant were matched to the time series data for the full sample (6,101 days).

Figure 5
Stationary time series of the BUX index

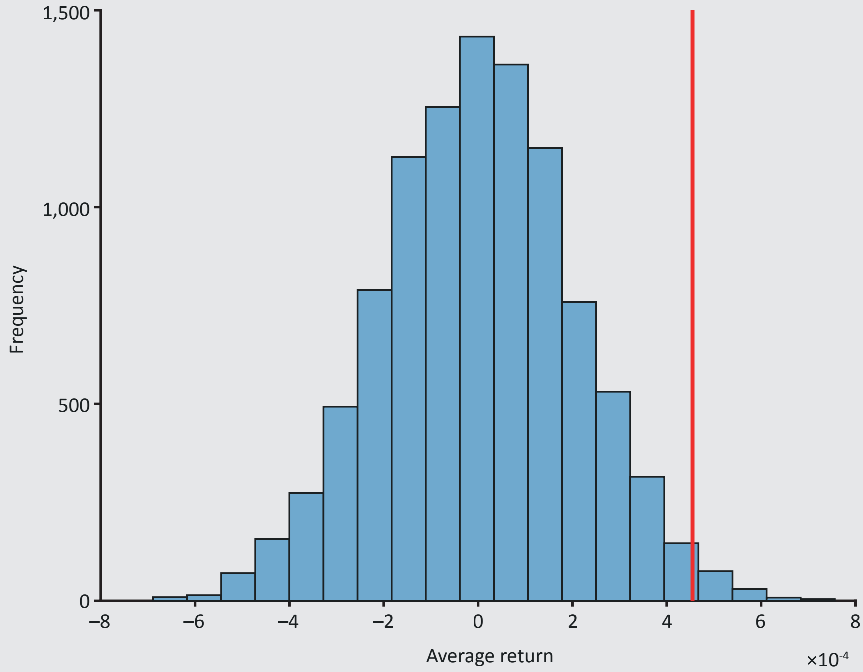


Note: The figure shows the time series of the BUX index data over the entire sample converted to a stationary time series based on formula no. 10.

After the above, the stationary daily returns were randomly mixed, and then the average daily return was calculated after matching with the output signals of model variant [110–7]. The data set was then repeatedly randomly (without replacement) mixed until 10,000 randomly generated time series and their associated average returns were available. *Figure 6* shows the average return for 10,000 randomly generated time series and the average return on the original time series. The p-value is 0.013, which is not sufficient to reject the null hypothesis.

The above shows that, although the variant [110–7] selected on the in-sample data outperforms both out of sample and over the whole period from the robustness point of view, the possibility that it may outperform due to randomness cannot be ruled out.

Figure 6
Histogram of the average return of 10,000 simulated cases



Note: The red vertical line representing the average return on the original time series.

7. Summary

The available literature differs on the predictive and outperforming ability of simple market timing methods. Intensive research on the subject is underway on simple moving average crossover signals. These studies are controversial, which is partly due to different methodology, out-of-sample data and lack of hypothesis testing.

Using the procedure described above, the results of 4,619 possible variants of moving averages were calculated on the stock index of the Budapest Stock Exchange, using 25 years of historical data, for in-sample, out-of-sample and full-period data. The results of each variants were compared with the return of the BUX index. In total, data from 554,935 transactions were processed. The separation of the data into in sample and out of sample and the pre-defined selection rules was necessary because without them, the variant trained on the historical data is automatically selected, given that the large number of combinations requires that one of the variants should fit the historical data well. However, this does not mean that the model can be used to obtain optimal results on future data (out of sample).

Taking into account a 0.3 per cent opening and closing trading cost on the in-sample data, 5.3 per cent of the 4,619 variants outperformed the benchmark index. The model variant [31–5] selected on the basis of the highest return on the in-sample data failed to outperform on the out-of-sample data. The model variant [110–7], selected on the basis of robustness criteria, outperformed both in sample and out of sample. Due to the low number of cases, it was necessary to perform a Monte Carlo simulation on the [110–7] variant. The results show that the null hypothesis cannot be rejected, i.e. the possibility that the outperformance of variant [110–7] is due to randomness cannot be excluded.

Based on the full period analyses, 45 per cent of the 4,619 variants outperformed when trading costs were not taken into account. Taking into account trading costs, only 9 per cent was able to outperform. The above suggests that moving averages may have some predictive power for the BUX index, but the method is very sensitive to trading costs, and thus it is questionable if it can be put into practice. Given that the results of the best model variant cannot be statistically confirmed as being significant, it cannot be said that simple trading rules based on the BUX stock index of the Budapest Stock Exchange offer a useful alternative to traditional investment strategies.

The above results also provided evidence of the limitations of the analysis of moving averages and market timing, since despite the long time horizon (25 years), the number of cases does not exceed 95 transactions in half of the model variants examined (2,323 variants). In addition to the above, the literature also raises the possibility that specific factors (e.g. investor sentiment, increased media attention, investor cognitive bias) may also affect the results of market timing methods (*Marshall et al. 2009; Li et al. 2023; Fernández et al. 2023*). These factors have also been studied in the domestic capital market, and results confirming international observations have been obtained (*Csillag – Neszveda 2020; Rádóczy – Tóth-Pajor 2021; Neszveda – Simon 2022*). In the continuation of the study, the results of timing strategies would be examined in the light of changes in investor sentiment and media attention, focusing specifically on this issue.

Despite the above, the results confirm the international literature, i.e. moving averages have predictive ability for market efficiency in the stock index of the Budapest Stock Exchange, which is located further away from the capital markets of developed countries. However, simple rules cannot be put into practice because of the trading costs involved. Notwithstanding the above, moving averages can be useful for investors in the stock market timing decision process.

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