

Study on the Applicability of Technical Analysis in the Czech Stock Market

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Abstract

There are many practitioners believing that the stock markets can be successfully predicted. To support their belief they provide examples of widely known successful traders. However, the existence of successful traders can be explained by the randomness and the huge number of other unsuccessful traders. As we never read about the unsuccessful ones, it may seem to us that the profitable predictions of the markets are possible and these predictions are due to the skill of successful traders, not due to their luck. In the paper we examine the applicability of technical trading rules in the Czech stock market, in particular we backtest the automated trading system based on moving averages crossover, optimize the parameters and statistically test the results for data snooping bias. In order to obtain valid results we assume transaction costs, address the riskiness and possible data snooping bias. We find that the optimized automated trading system outperforms the buy and hold strategy, but the statistical tests provide mixed results.

Keywords: automated trading system; efficient markets, moving averages; data snooping bias
JEL codes: G14, G17

1. Introduction

Among academics there is a broad discussion about a technical analysis. The technical analysis is a group of methods for evaluation of securities by analyzing statistics generated by market activity such as past prices and trading volumes. The prediction power of technical trading rules is often used as a test of the weak-form market efficiency. However, there is not a unified consensus on the profitability of technical trading rules (and the weak-form market efficiency at the same time). To name some studies see e.g. Brock et al. (1992), who applied simulation methods to test statistical significance of the profitability on Dow Jones Industrial Average market index in the period from 1897 until 1986 and found out that there exist significant risk-adjusted excess returns. On the other hand, Hudson et al. (1996) applied the same methodology in UK stock market in the period from 1935 until 1994 and they concluded that, although the examined technical trading rules do have predictive power in terms of UK data, their use would not allow investors to make excess returns in the presence of costly trading. Their results are thus in favor of weak-form market efficiency.

Another opponents of technical trading rules profitability are Scholz and Walther (2011), who studied the relationship between profitability of moving average rules and the characteristics of underlying price paths. They found that it is very likely for moving average trading rules to generate excess returns if the underlying price path exhibits negative drift, high serial autocorrelation, low and highly clustered volatility of returns. They concluded that there is hardly any prediction power but only a systematic reaction to the stochastic properties of the underlying price processes.

There are many others studies which both support and contradict the profitability of technical trading rules (and weak-market efficiency). For the review of studies published from 1960 until 2004 see Park and Irwin (2007). The authors found out that among a total of 95 modern studies, 56 studies find positive results regarding technical trading strategies, 20 studies obtain negative results, and 19 studies indicate mixed results. However, they also concluded that, despite the positive evidence of the profitability of technical trading strategies, most empirical studies are subject to various problems in their testing procedures such as data snooping bias, ex-post selection of trading rules or search technologies, difficulties in estimation of risk or omission of transaction costs.

On the other hand, there are many practitioners believing that the markets can be successfully predicted and even some well-known successful traders are presented as an examples. However, as it was clarified by Taleb (2008), the evidence of the successful traders can be explained by the randomness and the huge number of other (unsuccessful) traders. As we never read about the unsuccessful ones, it may seem to us that the profitable predictions of the markets are possible and moreover these predictions are due to the skill of successful traders, not just due to their luck. Imagine 1024 traders playing simple all-or-nothing game: they are guessing the direction of the next year price movement, they lose everything if they are wrong and they double the bet if they are correct. Assume that the half of the traders (the term gamblers would be probably more appropriate) always predict the upturn and the rest of them predict the downturn. Then, after the first year we observe 512 successful traders (each with 100% gain), after two years 256 successful traders (each with 200% gain) and after 8 years we observe four markets gurus each multiplying the initial wealth 256 times and being correct eight times out of eight. Moreover, by not considering the quantity of unsuccessful traders and the riskiness of the gamble these successful traders can be mistakenly considered as an evidence of the market predictability. Although the presented all-or-nothing game is unrealistic, it can serve as an example of perceived fallacy.

In the paper we examine the applicability of technical trading rules in the Czech stock market. The goal of the paper is to backtest the automated trading system based on moving averages crossover, optimize the parameters and statistically test the results for data snooping bias. White's reality check and Monte Carlo permutation test are applied for statistical testing.

The paper is structured as follows. In the following section we briefly describe applied methodology – we define trading systems based on moving averages crossover, explain the performance measures and the procedure of statistical testing. Then, in the next section we present the results of our empirical study.

2. Methodology

2.1 Trading Systems

In the paper we focus on the trading systems based on two moving averages crossover. Moving averages (henceforth MA) are trading rules which are well known by practitioners and popular example in academic literature. We can distinguish simple moving average, weighted moving average and exponential moving average. Further we will focus on simple moving average, which is nothing more than the simple average of last q prices,

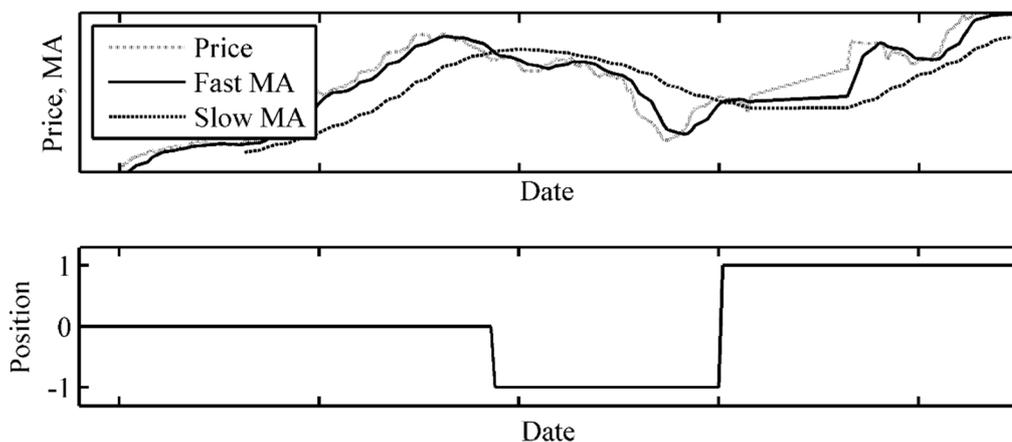
$$MA(q)_t = \frac{1}{q} \cdot \sum_{i=t-q+1}^t p_i \quad (1)$$

where p_i is the price at time i and $MA(q)_t$ is the value of the moving average at time t computed over last q periods. It can be noted that the weight of each price equals to q^{-1} , i.e. we compute simple average. The generally advised rule is to buy when the price crosses the value of moving average from below and sell when the price crosses the value of moving average from above. In order to filter the spurious signals and to lower the number of trades, trading rule can be generalized so that two moving averages are assumed: one called fast moving average with the low value of q and one called slow moving average with the high value of q . Denoting the periods of fast and slow moving averages as f and s the rule can be defined as follows,

$$x_t = \begin{cases} 1 & \text{if } MA(f)_t > MA(s)_t \\ -1 & \text{if } MA(f)_t < MA(s)_t \\ 0 & \text{otherwise} \end{cases} \quad (2)$$

The formula above represents an automated trading system (henceforth ATS) – an exactly defined procedure suggesting the position which should be taken: –1 for short position, 0 for neutral position and 1 for long position. The illustrative example of the described ATS is depicted in Figure 1. Although the presented ATS may look simple, it is widely applied by practitioners and in a contemporary area of interest for many researchers, see e.g. Anghel (2013) or Stanković et al. (2015). For the further details of the examined ATS see Kresta and Franek (2015).

Figure 1: The Illustrative Example of ATS Based on Two Moving Averages Crossover



Source: Kresta and Franek (2015)

2.2 Performance measures of the trading systems

Defining discrete returns r_t as a percentage changes of prices p_t ,

$$r_t = \frac{p_t - p_{t-1}}{p_{t-1}} \quad (3)$$

we can compute the wealth the investor would have possessed at time t had he/she followed the proposed ATS,

$$w_t = w_0 \cdot \prod_{i=1}^t \left[(1 + x_i \cdot r_i) \cdot (1 - f)^{|x_i - x_{i-1}|} \right] \quad (4)$$

where w_0 is the initial wealth – usually set to 1, x is the position taken according to (2), r is the discrete return computed according to (3) and f represents transaction costs stated in percentage which are incurred on buying and selling orders. Alternatively, the returns of trading strategy R_t^* can be obtained as follows,

$$R_t^* = \frac{w_t - w_{t-1}}{w_{t-1}} = (1 + x_t \cdot r_t) \cdot (1 - f)^{|x_t - x_{t-1}|} - 1 \quad (5)$$

Then, the Sharpe ratio (Sharpe, 1966) of the strategy can be easily computed as the ratio of the mean and standard deviation of returns R_t^* (the risk-free rate is assumed to be zero). The Sharpe ratio defines the profile of an investor who prefers titles with higher returns for unity of volatility (standard deviation). When comparing two assets versus a common benchmark (risk-free rate is generally assumed as the benchmark), the one with higher Sharpe ratio provides better return for the same risk or the same return for lower risk.

However, the standard deviation does not reflect the riskiness of the trading strategies well although it is in finance generally applied as the proxy for risk. The reason is that the increase in volatility of positive returns increases the standard deviation, but this can hardly be interpreted as the increased risk. The trader is generally more interested in downside risk measures such as semivariance, Value at Risk, Conditional Value at Risk, etc. One of the mostly applied risk proxies by practitioners is maximum drawdown, which is the worst decline in the wealth over analyzed period. If we assume wealth path $\{w_t\}_{t=0}^T$, we can compute the maximum drawdown over the period $(0,T)$ as follows,

$$\text{maximum drawdown} = \max_{t \in (0,T)} \left(1 - \frac{w_t}{\max_{\tau \in (0,t)} w_\tau} \right) \quad (6)$$

The maximum drawdown (henceforth MDD) is the worst decline in the wealth over analyzed period, i.e. the maximum relative difference between the peak value and the subsequent valley value. For further explanation see e.g. Chekhlov et al. (2005) or Magdon-Ismael et al. (2004) who studied the relationship between maximum drawdown and Geometric Brownian motion.

2.3 Statistical Inference about the Profitability of Automated Trading System

When making conclusions about the profitability of the ATS it is crucial not only to compute its final wealth or other performance measures, but also to judge whether the observed profitability is due to the predictive ability of the ATS or whether it is just due to the luck. The statistical testing is especially important in the case of ex-post analysis due to the possible data snooping bias (in literature also referred as to the data mining bias).

In the paper we apply the Monte Carlo Permutation test (henceforth MCP test) as described by Aronson (2006) and White's reality check (henceforth WRC test) as proposed by White (2000). Both mentioned tests consider the null hypothesis that all examined rules are useless, however, they differ in the way the uselessness is defined: in WRC test it is the case in which the returns of trading system are equal to zero or chosen benchmark while in MCP test it is the case in which the rule's signals are drawn randomly. Especially MCP test provides an interesting alternative to the traditional tests of market efficiency.

In accordance with Aronson (2006, p. 327-328) the procedure applied to generate sampling distribution of the final wealth (Sharpe ratio respectively) under MCP test can be described in the following steps:

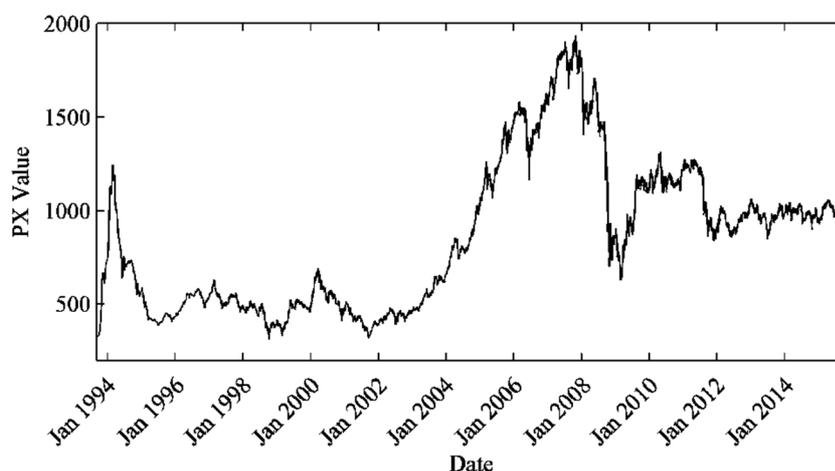
1. The daily rule outputs (vector of signals) of all n examined rules must be obtained.
2. Daily returns of the examined asset are randomly shuffled. By doing so we obtain the vector of scrambled returns.
3. Each rule outputs are paired with the vector of scrambled returns and the wealth paths are computed. We compute the final wealth (Sharpe ratio respectively) for each rule.
4. Out of these n rules we select the one with the highest final wealth (Sharpe ratio respectively). This value becomes the first value of the sampling distribution.
5. The steps 2-4 are repeated m times and the sampling distribution is formed. Aronson (2006) recommends to set m equal to 500 or larger number. In the paper we set $m=8,000$, which increases the time needed for computations but increases also the statistical validity of the results.
6. The p-value can be computed as a fraction of the values obtained by step 5 that are equal to or greater than the final wealth (Sharpe ratio respectively) of optimized automated trading strategy.

White's reality check, on the other hand, do not consider the signals of the trading rules and returns of the examined asset, but utilizes directly the returns of the trading strategies (5) which are bootstrapped applying Politis and Romano (1994) stationary bootstrap technique. There were published also other tests such as the superior predictive ability test (Hansen, 2005) or stepwise superior predictive ability test (Hsu, Hsu and Kuan, 2010), which are the extensions of the WRC test. The reader is referred to one of the above mentioned papers or original paper of White (2000) for technical description of the WRC test.

3. Data and Empirical Results

In the empirical study we assume the evolution of Prague stock market index (PX) in the period from September 7, 1993 until October 8, 2015. Applied dataset was downloaded from Prague Stock Exchange website (www.pse.cz) applying algorithm described in Kresta (2015). The evolution of the index value is depicted in the Figure 2.

Figure 2: The Evolution of the Prague Stock Market Index



Source: author's elaboration based on data from <http://ftp.pse.cz/Info.bas/Cz/PX.csv>

3.1 The Best (Ex-post) Parameters

In our paper we apply the automated trading system (2) to the downloaded data. We analyze all possible trading systems considering periods of fast moving average between one and fifty and periods of slow moving average between one and two hundred fifty. Thus, in total we consider 12,500 trading systems. Transaction costs are assumed to be 0.4% both for buying and selling orders. Basic characteristics of the ex-post performance measures of the analyzed trading systems are depicted in Table 1.

Table 1: Basic Characteristics of the Obtained Performance Measures

	Final wealth	Sharpe ratio	Maximum drawdown
Minimum	0	-0.329	0%
Maximum	8.76	0.037	100%
Mean	1.42	0.003	67.8%
Median	1.26	0.010	65.5%
Standard deviation	0.96	0.024	13.7%
Skewness	0.95	-3.00	0.44
Kurtosis	5.74	15.82	5.47

Source: author's calculations

The results presented in Table 1 represent basic characteristics of the performance measures of the 12,500 considered trading systems. We can see that there are trading systems which lost all the initial wealth (minimum final wealth 0 and maximum drawdown 100%) while the highest final wealth was 8.76, highest Sharpe ratio 0.037 and the minimum drawdown 0% (trading systems signaling no trades, e.g. those for which $f=s$). More importantly, we can see that on average the trading systems were profitable as both the mean and the median of the final wealth are higher than one (Sharpe ratio is positive). Moreover, it is obvious that the distribution of all three performance measures is skewed (skewness is non-zero) and heavy-tailed (high excess kurtosis).

The best trading strategy is the one with the period of fast moving average of 6 days and slow moving average of 26 days – this ATS has the highest value of both the final wealth and Sharpe ratio.

Detailed information are provided in Table 2. The average annual return (return of 250 consecutive days) is 10.6%, which is almost double the average annual return of the buy and hold strategy. The observed maximum drawdown was two-third of the buy and hold strategy. These results may indicate that the buy and hold strategy is outperformed. However, these are ex-post results, i.e. we fit the model (trading strategy) to data and then evaluate the performance on the same dataset, which can be the source of data snooping bias. In order to draw the correct conclusion, the proper statistical testing must be performed.

Table 2: Characteristics of the Optimized Automated Trading System

Characteristics	Automated trading system	Buy and hold strategy
Period of fast moving average	6	-
Period of slow moving average	27	-
Final wealth	8.76	3.1
Average annual return	10.6%	5.07%
Maximum drawdown	44.87%	74.61%
Sharpe ratio	0.0368	0.0208

Source: author's calculations

3.2 White's Reality Check

The returns of trading strategies computed according to (5) are first tested by means of WRC test. We performed two tests: i) a test whether we have found at least one profitable trading strategy, i.e. the benchmark is zero return, and ii) a test whether we have found at least one trading strategy that outperforms the benchmark (buy and hold strategy). In both cases we obtain the zero p-value and thus we reject the null hypothesis. As the null hypothesis is that we have not found an outperforming strategy, we can conclude that by means of White's reality check the moving averages crossover strategy provides an advantage and outperforms the buy and hold strategy.

3.3 Monte Carlo Permutation Tests

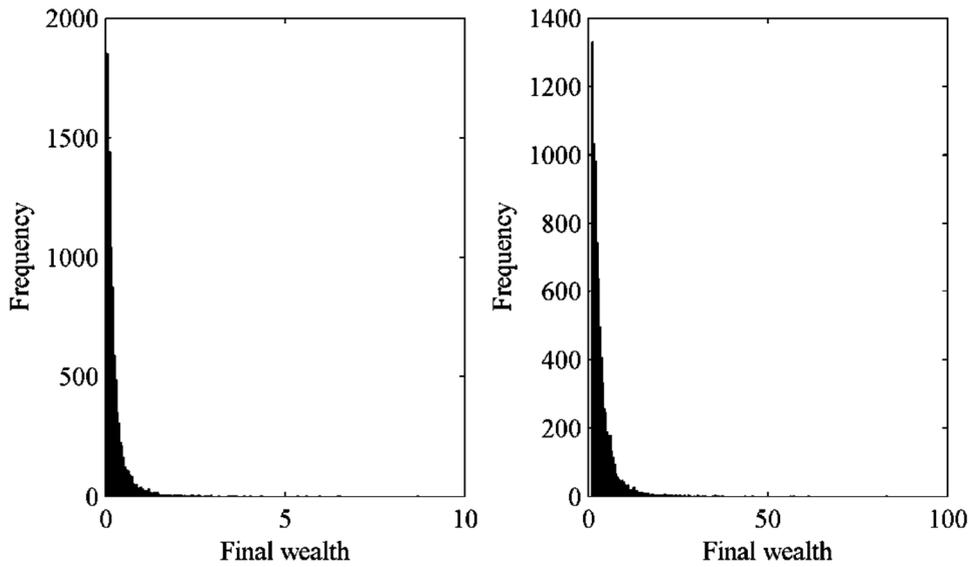
We apply MCP test as described in section 2.3. We permute the returns 8,000 times and for each permutation of returns we compute the final wealth and Sharpe ratio for all analyzed strategies. Then we form sampling distributions for both the final wealth and the Sharpe ratio. In order to illustrate the enormous impact of data snooping bias we formed also the sampling distributions when only the best strategy is considered – i.e. the sampling distribution do not consists of the maximum values over all the strategies, but it is formed as the values obtained from the best strategy when the returns are permuted.

3.3.1 Statistical Inference Based on Final Wealth

The histograms of the sampling distributions for the final wealth are depicted in Figure 3. The left graph represents the sampling distribution when only the best strategy is considered. In this case the p-value equals to 0 as in none out of 8,000 permutations the final wealth was higher or equal to 8.76. This may indicate that we can reject the null hypothesis (that the signals are drawn randomly) and conclude that we have found the outperforming strategy, however, as explained by Aronson (2006) this conclusion would not be correct as the results are biased.

When applying the proper procedure, i.e. taking the maximum final wealth over all the examined strategies, we obtain the p-value of 6.48% – in 518 out of 8,000 permutations the final wealth was higher or equal to 8.76. The p-value is higher than 5%, thus, the null hypothesis could not be rejected and we have not found the outperforming strategy. These findings correspond to the results presented in Kresta and Franek (2015).

Figure 3: Histogram of Monte Carlo Permutation Test for Final Wealth

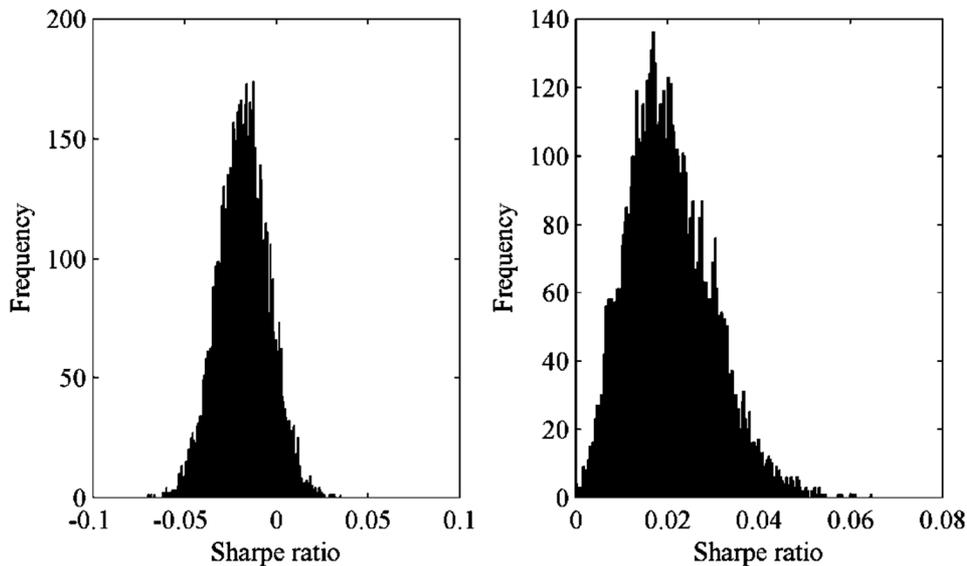


Source: author's calculations

3.3.2 Statistical Inference Based on Sharpe Ratio

The histograms of the sampling distributions for the Sharpe ratio are depicted in Figure 4. We again compute the sampling distribution when both only the best trading strategy (left histogram) and all trading strategies (right histogram) are considered. Both sampling distributions are constructed from 8,000 permutations of returns.

Figure 4: Histogram of Monte Carlo Permutation Test for Sharpe Ratio



Source: author's calculations

The p-value of the biased test statistics is 0 as in none out of 8,000 permutations the Sharpe ratio was higher or equal to 0.0368. However, when data snooping bias is taken into account, the p-value is 4.99% (in 399 out of 8,000 permutations the Sharpe ratio was higher or equal to 0.0368). Although we can reject the null hypothesis and conclude that the trading system with fast and slow MA periods 6 and 27 days provides statistically significant predictive edge (the signals are not drawn randomly), the p-value is very close to the 5% significance level and the results of statistical inference are thus disputable.

Also the shape of the sampling distributions is interesting. The left one (biased) can be fitted by normal (Gaussian) distribution, the mean is negative due to the transaction costs and the distribution is relatively symmetric. On the other hand, the correct sampling distribution (without the data snooping bias) is skewed, probably well-fitting by log-normal distribution and more importantly there are no negative values. The difference in these two sampling distributions represents the effect of the data snooping bias. It is obvious that we must pay attention to this effect.

4. Conclusion

When assessing the performance of technical analysis, the possible data snooping bias plays an important role. In the paper we examined the applicability of selected technical analysis rules on the Czech stock market index. In particular, we considered 12,500 trading systems based on moving averages and we applied White's reality check and Monte Carlo permutation test in order to draw a correct statistical inference.

The optimized automated trading system outperformed the buy and hold strategy in terms of both the profitability and riskiness. Note that the transaction costs were deducted and the maximum drawdown was applied as a proxy for riskiness. Considering these results we can conclude that if the investor had followed the optimized trading strategy he would have outperformed the market. However, the problematic point is that the parameters of the optimized strategy are known only at the end of analyzed period. Thus, in order to obtain valid conclusions, the statistical tests for data snooping bias were applied.

At first, we applied White's reality check. By means of this test we rejected the null hypothesis and concluded that we have found an outperforming strategy. This suggests that the performance of optimized automated trading system is not only due to the luck but it has the predictive power. We tried to confirm the result by means of Monte Carlo permutation test but we obtained mixed results. When we bootstrapped the final wealth, the null hypothesis could not be rejected and the test indicated that the predictive power was due to the luck only. When we bootstrapped the Sharpe ratio, the null hypothesis was rejected, which indicated that the automated trading system did possess the predictive power, but the p-value was close to the significance level.

Since the statistical tests provided mixed results it is difficult to make a single conclusion about the applicability of technical analysis in the Czech stock market. Although the White's reality check indicated that the technical analysis is applicable, we consider the results only as a symbolic due to the construction of the test's statistic. The results of Monte Carlo permutation test should be considered as more important. However, the results of this test are mixed.

To conclude, we were not able to statistically confirm the applicability of technical analysis in the Czech stock market. This indicates that the Czech stock market is efficient and the investors are not able to outperform it by following the automated trading systems based on the indicators of technical analysis.

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