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Analysis of moving average rules applicability in Czech stock market

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Abstract

Contemporary state of the art of financial time series modelling is connected to the Efficient Market Hypothesis according to which "prices fully reflect all available information" and hence future evolutions are unforecastable. In simple terms, EMH states that by predicting the future development we are not able to achieve the profits superior to the profits of the market index when these are adjusted for the risk and transactions costs are deducted. On the other hand, there exist works providing evidences that markets are not efficient. In these works, however, the strategies (or technical trading rules) are demonstrated to provide the extra performance in short term only and then the extra performance vanishes. In the paper we apply moving averages in order to define automated trading system and then analyze its profitability in Czech stock market. The results are statistically tested and statistical inference about the applicability of such an automated trading system in Czech stock market is made.

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Keywords: automated trading system; efficient markets, moving averages; data snooping bias

1. Introduction

Contemporary state of the art of financial time series modelling is connected to the Efficient Market Hypothesis (henceforth EMH) according to which "prices fully reflect all available information" and hence future evolutions are unforecastable, see e.g. Samuelson (1965). In simple terms, EMH states that by predicting the future development we

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are not able to achieve the profits superior to the profits of the market index when these are adjusted for the risk and transactions costs are deducted. Under this hypothesis, the investors can achieve higher profits only by taking higher risks.

One 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 amount 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 prediction are due to the skill of successful traders, not just due to their luck.

In the paper we examine applicability of technical trading rules in Czech stock market. In particular, we assume one of the most applied indicator – moving averages. The goal of the paper is to backtest the automated trading system based on two moving averages, 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.

The paper is structured as follows. In the following section we provide the reader with a short literature review. Then, in next section we briefly describe applied methodology – we define automated trading system based on two moving averages, explain the performance evaluation and the procedure of statistical testing. In the fourth section we present the results of our empirical study – the profitability of (optimized) automated trading system and the statistical inference about the data snooping bias.

2. Literature Review

Among academics there is a broad discussion about technical analysis. The technical analysis is a group of methods of evaluating 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 exists 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 and thus concluded that there is hardly any prediction power but only a systematic reaction to the stochastic properties of the underlying price process.

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 on 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 and omission of transaction costs.

3. Methodology

3.1. Automated trading system based on two moving averages crossover

Moving averages (henceforth MA) are trading rules which are well known by practitioners and a very popular example in academic literature. Generally, there can be distinguished 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,

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

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 $\frac{1}{q}$, 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,

$$decision_t = \begin{cases} \text{buy if } p_t > MA(q)_t \text{ and } p_{t-1} \le MA(q)_{t-1} \\ \text{sell if } p_t < MA(q)_t \text{ and } p_{t-1} \ge MA(q)_{t-1} \\ \text{do nothing otherwise} \end{cases} . \tag{2}$$

The 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 average as f and s the rule can be defined as follows,

$$decision_t = \begin{cases} \text{buy if } MA(f)_t > MA(s)_t \text{ and } MA(f)_{t-1} \le MA(s)_{t-1} \\ \text{sell if } MA(f)_t < MA(s)_t \text{ and } MA(f)_{t-1} \ge MA(s)_{t-1} \\ \text{do nothing otherwise} \end{cases} , \tag{3}$$

which results in two possible positions: short (we borrow the asset and sell it) and long (we buy the asset). Moreover we have to consider the neutral position (i.e. neither we are in short nor long position) which is held at the beginning of analyzed period due to the fact that we cannot compute the values of moving averages as we have not enough past data. The formula above represents simple automated trading system (henceforth ATS) – an exactly defined procedure suggesting whether to buy, sell or do nothing. The other definition of ATS can be as the function returning the position which should be taken: –1 for short position, 0 for neutral position and 1 for long position. Then, the system:

$$position_t = \begin{cases} 1 \text{ if } MA(f)_t > MA(s)_t \\ -1 \text{ if } MA(f)_t < MA(s)_t \\ 0 \text{ otherwise} \end{cases} , \tag{4}$$

is similar to (4). The illustrative example of the applied ATS is depicted in Fig. 1.

3.2. Profitability of automated trading system

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

$$r_t = \frac{p_t - p_{t-1}}{p_{t-1}} , \tag{5}$$

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

$$w_t = w_0 \cdot \prod_{i=1}^{t} \left[\left(1 + position_i \cdot r_i\right) \cdot \left(1 - fee \cdot \left|position_i - position_{i-1}\right|\right) \right], \tag{6}$$

where w_0 is the initial wealth usually set to 1, *position* is the position taken according to (4), r is the discrete return computed according to (5) and *fee* represents transaction costs stated in percentage which are incurred on buying and selling orders.

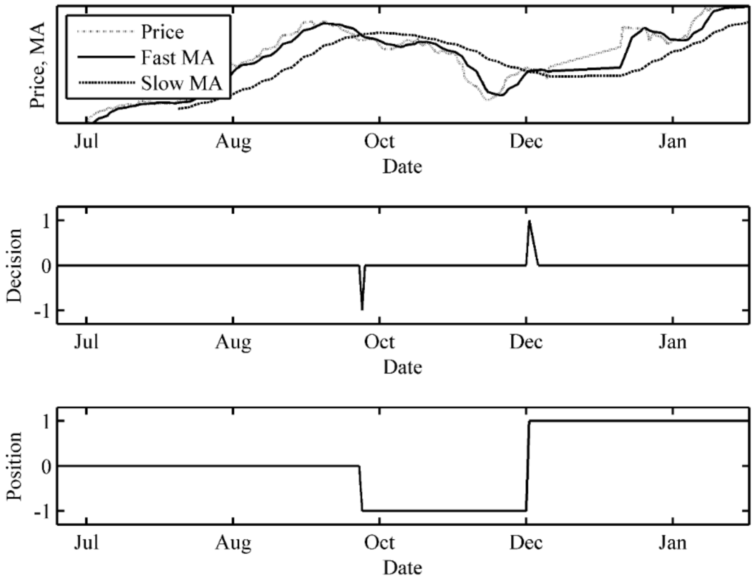

Fig. 1. The illustrative example of applied automated trading system

3.3. 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, 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). There are also other tests proposed in the scientific literature – for White's Reality Check (henceforth WRC test) see White (2000) and for test of superior predictive ability (henceforth SPA test) see Hansen (2005). All mentioned tests consider the null hypothesis that all examined rules are useless, however, they differ in the way the uselessness is defined: in WRC and SPA tests it is the case in which an expected return equals zero while in MCP test it is the case in which the rule's signals are drawn randomly.

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

1. Firstly, the daily rule outputs (vector of signals) of all N examined rules must be obtained.
2. Secondly, daily returns of the examined asset are randomly shuffled. By doing so we obtain the vector of scrambled returns. This step can be enhanced by applying stationary bootstrap technique of Politis and Romano

(1994) or applying historical simulation based on real market data as introduced by Tompkins and D'Ecclesia (2006).

3. Each rule outputs are paired with the vector of scrambled returns and the wealth path is computed.
4. Out of these *N* rules we select the one with the highest final wealth. This value becomes the first value of the sampling distribution.
5. The steps 2, 3 and 4 are repeated *M* times and the sampling distribution is formed. Aronson (2006) recommends to set *M*=500 or some large number. In the paper we set *M*=10,000, 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 of optimized automated trading strategy.

4. Empirical Results

In the empirical study we assumed the evolution of Prague stock market index (PX) in the period from September 7, 1993 until July 20, 2015. Applied dataset was downloaded from Czech National Bank (www.cnb.cz) applying algorithm described in Kresta (2015).

We applied the automated trading system (4) on the downloaded dataset and optimized the values of parameters, i.e. the periods over which slow and fast moving averages are computed, i.e. parameters *f* and *s* in (4). The feasible values were positive integers lower than 50 (fast MA) and 250 (slow MA). For each combination of fast and slow MA we computed the vector of signals and the wealth evolution over the analyzed period. Transaction costs were assumed to be 0.4% both for buying and selling orders. In Fig. 2 we depict the values of the wealth the investors would have possessed at the end of analyzed period (July 20, 2015) in the case that they had invested one Czech crown at the beginning of analyzed period (September 7, 1993) and they had followed optimized automated trading system.

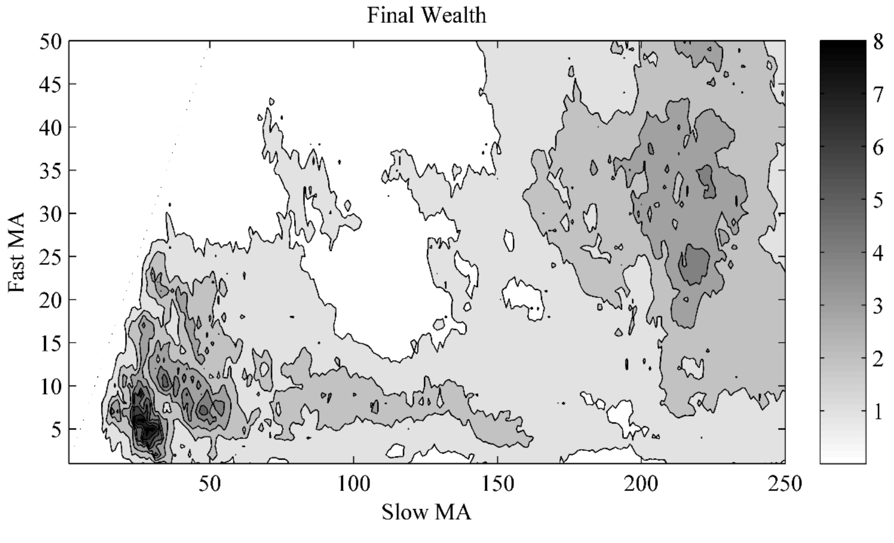

Fig. 2. The values of final wealth in dependence on MA periods

As can be seen in Fig. 2, the good set-ups would be periods of 4-6 days for fast MA and periods of 26-30 days for slow MA. The best set-up was 6 days for fast MA and 27 days for slow MA. The comparison between best ATS and buy and hold strategy is discussed further (see Fig. 3 and Table 1).

Moreover, from the figure we can see that the strategies, for which the period of fast MA is higher than the period of slow MA, lost almost whole initial investment. This finding suggests that the logic of the proposed automated trading system is correct – i.e. to follow the trend. The strategies, for which period of fast MA is higher than the period of slow MA, can be viewed as the strategies betting on the price reversals.

There is also one imperfection of the visual representation of the obtained results: all the strategies, for which the period of slow and fast MA are equal, deliver final wealth of one, although it is not clear from the figure (due to the applied interpolation of the data between integers).

Table 1. Characteristics of the optimized automated trading system and buy and hold strategy.

Characteristics	Automated trading system	Buy and hold strategy
Period of fast moving average	6	-
Period of slow moving average	27	-
Final wealth	8.57	3.1
Average annual return	10.6%	5.45%
Maximum drawdown	44.87%	74.61%
Sharpe ratio	0.0368	0.0218

Basic characteristics of the automated trading system are depicted in Table 1 whereas the evolution of wealth path (cumulative profits) is depicted in Fig. 3. In both the table and the figure the results of ATS are compared to buy and hold strategy. As can be seen, if the proposed active strategy is followed, both the average annual return increases and maximum drawdown decreases compared to buy and hold strategy (presented results take into account transaction costs of 0.4%). Also, Sharpe ratio of the ATS is higher than the Sharpe ratio of buy and hold strategy. These results may suggest that the proposed automated trading system provides positive extra performance while risk is decreased, i.e. that the further development can be predicted to some extent and Czech stock market is inefficient. However, before making this conclusion the proper statistical analysis should be made.

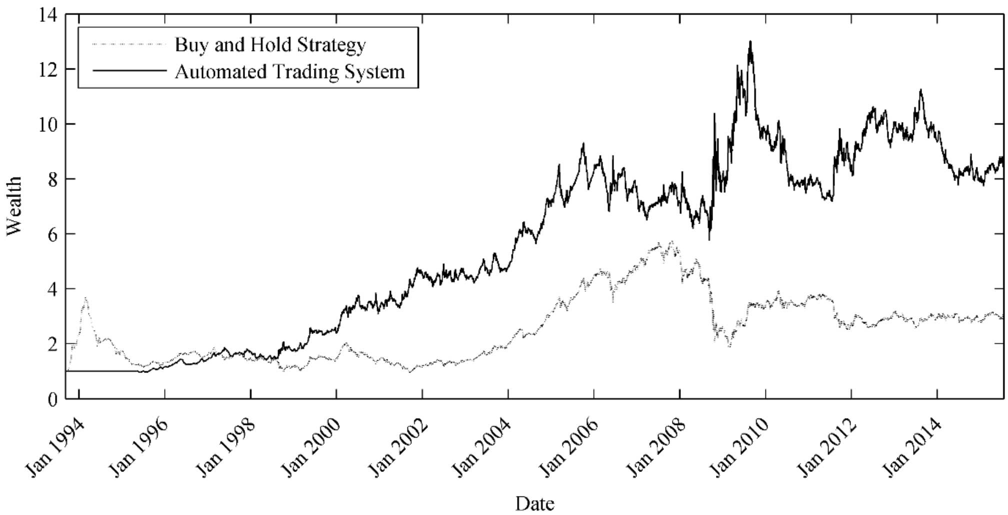

Fig. 3. Evolution of wealth in time following buy and hold strategy and automated trading system

In the paper we apply the MCP method proposed by Aronson (2006) and described in section 3.2 of the paper. The number of examined rules N is 12,500 (all combinations of fast and slow MA) and we permuted the returns 10,000 times, i.e. M=10,000. The computations were performed in Matlab and the time requirement was approximately 14 hours of CPU time. Considering all 12,500 rules we obtain the p-value of 5.52%. It means that on 5% significance level we cannot reject the null hypothesis that the rule's signals are drawn randomly (there is no predictive power of the trading rules). However, the p-value is close to the chosen significance level (5%) which gives rise to the need of further research and statistical testing.

Moreover, as the quantity of trading rules included in the analyzed universe plays role, we examined the effect of this quantity on the resulting p-value. The results are depicted in Fig. 4. On the horizontal axis there are the quantities of trading rules (i.e. different combinations of fast and slow MA) incorporated in the analyzed universe and on the vertical axis there are the corresponding p-values. The trading rules are sorted as follows: the first rule is rule 1-1 (i.e. both fast and slow MA of 1 day), the second rule is 1-2 (i.e. fast MA of 1 day and slow MA of 2 days), 250^{th} rule is 1-250 (i.e. fast MA of 1 day and slow MA of 250 days), 251^{th} rule is 2-1 (i.e. fast MA of 2 days and slow MA of 1 day), 500^{th} rule is 2-250 (i.e. fast MA of 2 days and slow MA of 250 days), etc. As can be seen from the figure, the p-value increases mostly in the range of 100-250 and 350-500, at the value of 1,000 reaches its maximum and then decreases. The range, in which p-value increases, represents the rules which are the most prone to data snooping bias. On the other hand, the range in which p-value decreases represents the rules which are not prone to data mining bias. The optimized automated trading system (i.e. fast MA of 6 days and slow MA of 27 days) is the $1{,}277^{th}$ trading rule, i.e. it is in the area of trading rules which are not prone to data snooping bias.

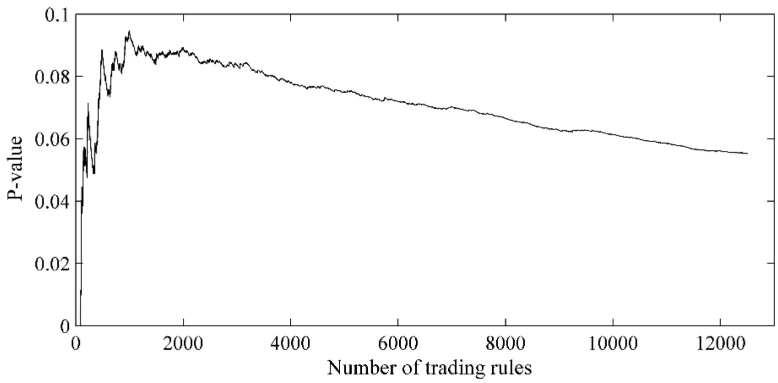

Fig. 4. The dependence of the resulting p-value on the size of trading rules universe

5. Conclusion

Among academics there is a broad discussion about the profitability of technical analysis. There are proponents as well as opponents, both groups providing empirical evidences of the (un)profitability of the automated trading systems based on technical analysis rules. In the paper we examined applicability of technical trading rules in Czech stock market. In particular, we backtested the automated trading system based on two moving averages, optimized the parameters and statistically tested the results for data snooping bias. In order to obtain valid results we assumed transaction costs and addressed the riskiness and possible data snooping bias.

We found out that the system, which is based on crossover of two moving averages, is profitable even after deduction of transaction costs of 0.4%. We found out that the proposed strategy delivers higher average annual return while decreases maximum drawdown in the analyzed period as compared to buy and hold strategy. However, as we performed ex-post analysis, particularly problematic was the fact that we optimized the system on the same dataset from which we drew conclusion about the profitability, it must have been ensured that the results are not biased due to the data snooping phenomena.

We applied the Monte Carlo Permutation test whose null hypothesis is that the rule's signals are drawn randomly. Considering the universe of 12,500 automated trading systems we were not able to reject this null hypothesis. However, the p-value was very close to the chosen significance level, which makes the conclusion disputable and gives rise to the need of further research and statistical testing.

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