The Review of Finance and Banking
Volume 05, Issue 2, Year 2013, Pages 089–115
S print ISSN 2067-2713, online ISSN 2067-3825

HOW RELIABLE IS THE MOVING AVERAGE CROSSOVER RULE FOR AN INVESTOR ON THE ROMANIAN STOCK MARKET?

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Abstract. Applying a technical analysis trading system based on the moving average crossover rule for companies listed on the Bucharest Stock Exchange does not produce significant profits, but leads to consistent excess returns and lower risk versus the benchmark buy and hold strategy for a potential investor during the 2001-2011 period. Comparing the results with the ones obtained for companies listed on two more developed markets, the United States and South Korea, a significant return surplus on the local market can be identified. The results point out that the local market is less efficient than the two foreign ones but also that the Romanian stock market is not weak form informational efficient.

1. Introduction

Technical Analysis is an old investment method. Despite of this, it's highly practical and mostly unscientific approach makes it the Cinderella of investment methods among scholars. Its utility as an instrument of investment decision making has been ignored, although it is widely used among financial market practitioners. Most brokers all over the word, including Romania, issue regular technical analysis reports. Also, Taylor and Allen (1992) report that more than 90% of investors in the foreign exchange market use technical analysis in tacking buy-sell decisions. Recently, Menkhoff (2010) observed that large portfolio managers on the stock market in several developed countries use technical analysis in the decision making process, and that this method dominates over fundamental analysis for decisions regarding shorter time intervals.

In essence, technical analysis tries to forecast the future movement of traded assets using only their past trading data. This evidently contradicts the postulates even in the case of the week form EMH. This type of analysis has a long history and dates back to the Japanese rice traders trading on the Dojima Rice Exchange in Osaka as early as the 1600s[1]. Despite of this, it only gained popularity among investors in the western financial markets in the late 19'th century when Charles H. Dow, founder of The Wall Street Journal, wrote a series of articles investigating its use. The academic community continued to ignore it throughout the first part of the 20'Th century and most of the second part, and, with a few passionate exceptions, it only began shifting its attention towards it when compelling evidence against the EMH began to emerge.

Over the years, scientific studies regarding the utility of technical analysis have been scarce, mostly because of the efficient market (EMH) paradigm, which rules out using historical trading data for obtaining future excess returns. Also, the few papers that had been written were focused on big financial markets, especially the United States, and had severe methodology problems.

Received by the editors December 3, 2012. Accepted by the editors November 30, 2013.
Keywords: Investments, Trading, Technical Analysis, Indicators, Momentum, Moving Averages, Bootstrap.
JEL Classification: G11, G14.
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This paper is in final form and no version of it will be submitted for publication elsewhere.
[1]Wong, Manzurd an Chew (2010), p.1.

This, however, is unexplainable, because as Fama and Blume (1970) point out "[...] the ultimate criterion is always practical". Only in recent years have things began to change, when severe problems with the EMH have come to surface and the new discipline of Behavioural Science, one that takes into account the psychological impact on financial prices (the same as technical analysis), began to gather more and more followers.

Among the first distinguishable empirical studies that can be mentioned are that of Alexander (1961) and Fama and Blume (1966), but those can now be categorized as primitive. Only in the 1990's have more serious works appeared, with Lukac, Brorsen and Irwin (1988) leading the way. Their methodology, inspired from practice, divided the data sample in two, used in sample parametric optimization to find the best performing rule from a set of technical trading rules known as a universe of rules and then applied this rule to the out of sample data. They then tested the results using some standard econometric tests.

Recently, Brock, Lakonishok and LeBaron (1992), White (2000), Romano and Wolf (2005), Hansen (2005), Hsu, Hsu and Kuan (2008) or Bajgrowicz and Scaillet (2009) worked on improving the testing methodology regarding this particular subject, bringing it in line with modern requirements.

Some parallel approaches to testing technical analysis have also been tried, among which the most important are Neural Networks, Genetic Programming and Markov Chains, but there are still many things to sort out with these, given the relative small number of such studies.

As to this author's knowledge, a theoretical or empirical study regarding the usefulness of technical analysis methods for the investment decision process on the Romanian stock market has not been performed, although there have been a number of studies regarding information efficiency. Todea and Zoicas-Ienciu (2011) investigated the profitability of a technical trading system based on the moving average crossover rule for the Romanian foreign exchange market, i.e. for the EUR/RON trading pair from 1999 to 2008, reporting consistent positive returns despite of the gradual raise in liquidity levels over this period. However, their reported returns were not cost and risk adjusted.

Thus, a paper studying the profitability of technical analysis methods on the Romanian stock market is highly sought. It would be important not only for the investors seeking opportunities on the local market, but also for the academic community, because it would bring new evidence regarding the informational efficiency of the Romanian financial market, which is a fairly young one.

This paper aims to cover three issues. First of all, it aims to investigate the opportunity of using some simple technical analysis trading systems based on the moving average crossover rule for obtaining profits on the Romanian stock market, but more important, for obtaining excess risk and cost adjusted returns versus the buy and hold strategy. Secondly, it aims to express some ideas regarding the degree of information efficiency of the local market, which depends on finding or not economic relevant trading systems. There is a direct negative relationship between technical trading system relevancy and the degree of weak form market efficiency. Last but not least, given the degree of research in the area of technical analysis among the local scientific community, it aims to promote technical analysis practical methods as important decision making investment tools, but also to accustom the local readers with the specific scientific methods for studying this field.

Given this objectives, this article is organized as follows: section 2 discusses the testing method used, which, being a simulation of the actual practitioner's routine, is different from the standard methods used thought most papers in the field. It also covers the sample data used in the tests that were performed. Section 3 presents and explains the results. Section 4 concludes.

2. Testing method and sample selection

2.1. **Methodology overview.** The scientific approach of investigating technical analysis must remove the subjective elements and issue judgments on the purely mechanical methods, the human factor being very difficult, if not impossible, to model. Thus, the preferred method of researchers is that of technical indicators, which have consistent computational formulas, although the chart pattern method can successfully rival it. Also, a non-discretionary approach is a mandatory condition for scientific research.

Taking all of these into consideration, researchers who have studied technical analysis have tried to show the relevance of using technical indicators for obtaining *economic returns*[2]. Most of them have started with the practitioners' method, where a certain system is backtested on historical data and if it generates satisfactory results it is then applied in future trading[3]. Moreover, they test a large group of systems, called a universe of trading rules or a universe of trading systems, choosing to use in the investing activity the one that obtained the best results on historical data. In other words, they optimize the rule based on a given target return indicator (which can be viewed as a function) by iterating each possible parameter combination for the initial trading system in order to find the most profitable parameter combination for the past period. From the scientific point of view such an approach involves the appearance of a *data snooping bias*[4] which may lead to choosing a system that was simply lucky in the past but does not have an actual economic relevance, so that it does not guarantee obtaining similar results in the future. Therefore, the actual problem when choosing a trading system is that of the consistency of its results. For a trading system to be considered economically relevant, it must:

1. obtain economic returns;
2. these have to be time-consistent;
3. these also have to be consistent in space[5].

In order to test these characteristics, researchers have developed several methods, these being very well synthesized by Cheol-Ho Park and Scott H. Irwin (2007): *the standard method* (in sample optimization followed by out of sample confirmation), *bootstrap confirmation method* (based on the methodology introduced by Brock, Lakonishok and LeBaron, 1992), *genetic programming* (where researchers attempt to eliminate the data snooping bias by implementing genetic algorithms introduced by Koza, 1992), *the reality check* (based on the Bootstrap Reality Check methodology introduced by White, 2000)[6] and other *non-linear methods* (such as *feed forward neural networks* or *k-Nearest Neighbours regressions*).

This paper implements the standard testing method, but the results are also confirmed using a non-standard bootstrap testing methodology. The arguments for this choice and the testing procedure details are presented in the following paragraphs.

2.2. **Testing method.** In this paper the Standard method is used as the main testing method. This means that the data samples are divided into two sub-samples, the best system from the trading universe in the first sub-sample is chosen using optimisation of the target return measure and then the results are confirmed on the second sub-sample. There are two main reasons for choosing this testing method: first of all, the method is the simplest of the available ones, making it very useful for a first examination of data from the Romanian stock market; but more importantly, this method mimics what practitioners actually do, so it may be considered more relevant. However, it does not quite meet all scientific standards for statistical confirmation of the results, mainly because it does not take into account the possibility of estimator bias due

[2]Economic returns refer to returns adjusted to total trading costs and risk that are higher than the ones obtained by a competing benchmark strategy.

[3]This is based on the third principle of technical analysis.

[4]This is also known as *data mining bias* or *overfitting*.

[5]Consistent in space means to fulfil the first and second conditions for several asset classes and in several markets. This condition is not supported by the author, since it involves a universal and absolute character of technical analysis and, therefore, of market efficiency, while in reality efficiency seems to have a relative character, differentiated from one market to another and from one asset to another. Empirical studies like Hsu and Kuan (2005) support the relative approach.

[6]The reality check was further improved by Romano and Wolf (2005), Hansen (2005) and Hsu, Hsu and Kuan (2009).

to data snooping. Thus, a second procedure is implemented for confirming the results, this being based on a non-standard bootstrap test which will later be detailed. Implementing this approach generates some questions, each of these being discussed next.

First of all, there is the question of the measure used for quantifying returns. In theory, only economic results matter. However, the academic and practitioners literature uses a multitude of indicators for this purpose, each with their own advantage and disadvantage. In this paper, the *geometric M2 for Sortino excess return* (denoted ExM2s)[7] is used. Being recently developed, this measurement combines several important characteristics[8]: (a) it computes an excess return, in the sense that it compares the result obtained by the trading strategy used by the investor with a benchmark strategy and reports the excess performance. (b) The results are adjusted to risk, but not total risk, as is usually used in the literature, but downside risk (the specific risk of portfolio depreciation), this being the really important risk for an investor[9]. In other words, the results are adjusted by the risk differential of the investment portfolio compared to the benchmark portfolio, thus answering the question "What would have been the performance obtained if the investment strategy had the same risk as the benchmark strategy?" For instance, if the investor's portfolio risk is lower than that of the benchmark portfolio, the investor's adjusted performance to risk will be higher than the one effectively obtained. (c) It is an indicator whose values are easy to interpret by any investor, since it quantifies the geometric difference between the portfolio return and the return of the benchmark strategy. The geometric approach is more useful than the arithmetic approach because it gives a ratio advantage[10] and more[11].

Secondly, there is the question of interpretation. What would the results say about the informational efficiency of the Romanian stock market? A hypothesis derived from the most recent empirical studies states that informational efficiency is a relative concept, specific to each market and is not a universal concept[12]. Thus, a clearer image on the results on the local market may be formed if we would test other external markets as well. In this respect, issuers from two additional stock markets, namely the United States and South Korea, are chosen for testing the same technical analysis systems and comparing the results. These two markets are chosen because they are much different from the Romanian one, with the US being the largest stock market in the world, while the Korean one being one of the most developed stock markets in Asia. The profound differences in maturity, structure, size, functioning mechanisms and investment habits would maximize the chance of obtaining heterogeneous results that may prove the above stated relative concept and would show how the Romanian stock market compares to two of the world's most influential ones.

Last but not least there is the question of the benchmark. This study uses the "buy and hold" strategy as a benchmark strategy. Apart from the fact that it is the natural strategy for

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[7]This is a hybrid indicator combining the characteristics of the Modigliani-Modigliani indicator for measuring risk adjusted performances (M2) with the Sortino rate that incorporates a measurement for downside risk.

[8]Carl Bacon (2008) offers a more detailed discussion regarding this indicator.

[9]Historically speaking, risk is measured by total variation. But an investor with an open position in the market will be concerned mostly with negative variation of his portfolio value, while the positive variation is quite welcomed.

[10]For example, when the returns are -5% for the benchmark and 5% for the portfolio, the arithmetic excess would be 10%. The same thing would happen when they are 1000% and 1010%, but the situations have a completely different interpretation. In these cases, the geometric excesses returns would be 10.25% and 0.91%, values that better represents the situation.

[11]For details, please see Carl Bacon (2008), p. 52-55.

[12]For example, Hsu and Kuan (2005) find that some technical analysis rules have predictive power in relative "young" markets, but not in relative "mature" markets. Also, many studies reviewed by Park and Irwin (2007) report heterogeneous results among the analyzed samples. The evidence lead to the point when Lu (2009) conceptually dismisses the absolute EMH because it is not empirically refutable since its proposition is open to any information that has been reflected in security prices but exclusive of the information that has not been reflected in security prices, while the relative EMH is the only empirically refutable concept because it is confined to a particular information space.

comparison, it is also the embodiment of the theoretical investment method on an informational efficient market[13]. If the market price embodies all available information at any given time, what point would it make to an investor to spend time and capital for obtaining information and thoroughly analysing it, not knowing what the future evolution of the asset price might be. The buy-and-hold strategy buys the asset at the initial moments and holds it up to the final evaluation moment. Unlike it, any other strategy, including the technical analysis ones which will be investigated in this paper, are based on active trading to speculate the permanent price fluctuations in order to obtain a superior performance to the passive strategy.

2.3. **Category of tested trading systems.** As it was stated previously, technical analysts have a large range of indicators to choose from when building their own trading system, thus they can build an infinity of trading systems based either on one technical indicator (and choose the adequate parameters) or on several of them, each bringing their own information surplus to the investment decision. However, the great majority of investors are familiarized with only a small number of indicators so they choose to use only one or a limited number of indicators, for which they specialize over time. Based on this reason, this study tests a single type of systems, based on the moving average cross-over rule. This is easy to use, intuitive, but also very popular in practice.

These types of systems are composed out of two moving averages, a short term one and a long term one. Technical analysts argue that when price moves upwards, the short term moving average will rise faster than the long term one (the latter being less responsive to recent price changes), indicating buying pressure and the possibility of a future bullish trend. Thus, as long as the short term moving average values will be above the long term moving average ones, a market that favours growth will be indicated. For the investor, this means that he must open a long position: he will buy the asset when the short term average will cross over the long term one and will maintain the position until the short term average will cross under the long term one. By applying the same reasoning, the investors will sell short and will maintain the selling position as long as the short term moving average is below the long term one. Mathematically, the buying signal for this type of rules can be represented as:

$$MA_1(n_1) > MA_2(n_2) \tag{2.1}$$

The type of trading system resulting in this way has two parameters: the computational period for the short term average - n_1 - and the computational period for the long term average - n_2. The integrity condition is $n_1 < n_2$. Since, in practice, there are several types of moving averages which can be used, the short term average is chosen to be of an exponential type ($MA_1 \equiv EMA$[14]) and the long term average of a simple type ($MA_2 \equiv SMA$[15]). This choice is meant to increase the reaction time of the short term average to new price movements, thus attempting to obtain trading signals as soon as a new trend begins. However, the choice does not have a theoretical base, but the differences resulting from using other average types should not be significant, much more important to trading success being the choice of parameters.

2.4. **International evidence on the reliability of the moving average cross-over rule.** The moving average cross-over rule is one of the first technical trading rules that have ever been tested by scholars. It is also one of the most frequently employed rule in testing. This can clearly be seen in Park and Irwin (2007) where the overwhelming majority of reviewed studies employ this specific rule as part of the trading universe. The tests cover a wide variety of asset classes (stock, commodities, futures, currency) and employ a wide variety of methodologies, although there are concentrated on developed markets. For example, Cootner (1962) tested this rule

[13]The Martingale process used in modelling efficient markets postulates that the expected value of an asset performance is non-negative, thus, the best way to maximize long-term portfolio value is to buy and hold the asset.

[14]Exponential Moving Average.

[15]Simple Moving Average.

on 45 NYSE stocks and found that the returns generated do not significantly differ from the buy-and-hold strategy. Alexander (1964) tested it on S&P Industrials and found that after deducting trading costs, the returns do not surpass that of the buy-and-hold benchmark. Irwin and Uhrig (1984) tested this rule on 8 commodity futures and found that it was profitable even in out of sample trading. Neftci and Policano (1984) tested it on 4 futures contracts and found that they had predictive power in some situations, especially for T-bills, gold and soybeans. Taylor (2000) found this rule to be economically relevant for several tested US and UK asset classes. Gunasekarage and Power (2001) tested it on 4 Asian stocks and found that it generated significant returns above the buy-and-hold benchmark for buy trades and below it for sell trades. Olson (2004) found the moving average cross-over rule to generate positive returns for several currency pairs, but discovered that profits have declined over time. In general, the reviewed papers showed mix results (58 positive, 10 mixed and 24 negative) regarding the profitability and predictive power of technical analysis rules, including moving average crossover ones, for stocks, commodities, futures and foreign exchange markets.

This did not change in recent papers, after Park and Irwin (2007) were published, independent of the categories of tested markets and asset classes, although fewer published papers exist because more sophisticated testing methods were employed that shifted the attention from the classical technical analysis rules to more complex ones (by means of neural network or genetic optimisation). Zhu and Zhou (2008) showed that when stock returns are predictable, moving average rules add value to commonly used allocation rules that invested proportions of wealth in stocks. Papathanasiou and Samitas (2010) tested the moving average crossover rule on the Cyprus Stock Exchange and found that when transaction costs are ignored, this significantly outperform a buy-and-hold strategy over the 1998–2005 period. Kannan et. al. (2010) tested some simple technical analysis trading rules, including the moving average crossover one, and compared them to the results of their proposed new combinatorial algorithm (BSRCTB). They found that there is some validity to technical analysis of stocks. Heyman, Inghelbrecht and Pauwels (2012) investigated the performance of several technical analysis rules, including moving average cross-over ones, on 34 Emerging Stock market indices and found that most of them do not outperform naïve buy-and-hold rules, although 4 significant exceptions are found. The reported results leads them to the idea that technical analysis is more profitable in crisis situations.

Overall, researchers have not established thus far if the moving average crossover rule is economically relevant. It seems that the results widely vary and this is due to tree independent reasons. First, the markets that were tested are heterogeneous, this pointing out that the applicability of certain technical analysis indicators is tied to individual markets. Secondly, the temporal samples widely vary. This coupled with the variety of results suggests that market efficiency changes trough time, thus pointing out that the Adaptive Market Hypothesis should be considered for financial markets. Finally, there is a diversity of employed methodologies. This generates some risks for the reported results. On one hand, there are authors that do not consider data snooping risks in their analysis, do not test for statistically significance of results, do not perform out of sample confirmation or, even worse, do not adjust their results to trading costs and/or risks. These practices can clearly lead to false discoveries. On the other hand, there are those that exaggerate with restraints on their methodology trying at all costs to avoid the negative effects of data mining. These then fall into another trap, because they stray away from investment practice and report some results that are not useful to common practitioners of technical analysis. This study tries to avoid both common pitfalls by using a non-standard testing and confirmation methodology.

2.5. **Data samples used in testing.** The data sample is comprised out of daily trading series for 37 companies listed on the Romanian, the United States and South Korean stock markets, starting with January 1, 2001 and up to October 31, 2011. Out of these, 17 companies are listed on BVB, 10 on NYSE and 10 on KRX. The companies are chosen using the importance criterion, expressed by their market value. Moreover, for the Romanian companies, the liquidity criterion is also important because out of the one hundred or so listed companies, only a few have sufficient liquidity for technical analysis to be applied.

The data is collected from free access sources, i.e. the SSIF Broker webpage *http://www.tranzactiibursiere.ro/* for Romania and the Yahoo! Finance webpage *http://finance.yahoo.com/* for the United States and South Korea. The daily price series are adjusted with the effects of capital changes and dividends. For the external companies, the data source already reports adjusted prices, while for the Romanian companies a supplementary adjustment procedure is needed, this being based on the data reported on the Bucharest Stock Exchange webpage *http://www.bvb.ro/* for each issuer, in the sections *Financial data – Dividends and Share Capital Changes*. An automated algorithm is used to adjust the data for the Romanian companies.

2.6. **The testing procedure for a single data series.** In order to have accurate results, a testing procedure is implemented to mimic the investment procedure of an actual trader. In this respect, fictive investment portfolios are created with an initial arbitrary value of 10,000 RON in the case of Romania, 10,000 USD in the case of the United States and 10,000,000 KRW in the case of South Korea. In order to show the market position, a signal function is created by applying the cross-over rule previously presented. The signal function thus resulting is of the form:

$$S_i = \begin{cases} 1,\ if\ EMA\left(n_1\right) > SMA(n_2) \\ 0,\ if\ n_1 < i\ \ and\ n_2 < i \\ -1,\ if\ EMA\left(n_1\right) \leq SMA\left(n_2\right) \end{cases} ,\ i \in (1, T) \tag{2.2}$$

where i represents the moment of the signal computation, measured in daily observations and T is the total number of observations. The signal value represents the total percentage of capital allocated at moment i in a market position. Given the above definitions, the following characteristics of the chosen trading systems can be observed:

- $S_i \in [-1, 1]$.

- They have permanent market exposure, except for the case when $i < n_1$ and $i < n_2$, that is, when the moving averages cannot be computed; otherwise, $S_i = 1$ (we have an open buying position) or $S_i = -1$ (we have an open selling position).

- They have 100% allocated capital at any moment. This means that the entire portfolio is engaged in the market and there is no reserve capital available for other purposes. In other words, the trading systems do not have a capital allocation component[16].

- There are cases when $S_i < 0$, so it is assumed that short positions can be opened.

- A trade is generated when the signal function changes its value: if $\Delta S_i > 0$ we have a buy order at moment i and if $\Delta S_i < 0$ we have a sell order. So, we have instant trading at the moment the signal appears.

Starting with the signal function and its suggested trades, the portfolio function (V_i) can be calculated. This is influenced by the market price changes and the market position indicated by the signal function. The trades first of all change the market position, but they also directly impact the portfolio value through trading costs. In order to have a relevant testing procedure and to avoid a bias in the return estimators, the trading costs are taken into consideration[17]. These vary around 1% of trade value when investing with retail Romanian brokers, while for the

[16] If it would have existed, we could have found cases where, for instance, Si = 0,5 which meant investing 50% of total available capital, so that for a portfolio value of 10,000, only 5,000 were engaged in the market, while the rest were kept as a backup or for investment in a different asset.

[17] Many empirical studies, including Timmermann and Granger (2004, p. 16), showed the importance of taking into consideration trading costs. In an ideal test, a researcher must include both observable costs (commissions, fees, etc.) and non-observable costs (bid-ask spread). This study adjusts the returns with known observable costs, but also with part of the non-observable costs by trading at the least favourable market prices. This approach is more reliable in generating non-biased return estimators, although, to the author's surprise, it is scarcely used in the fields.

United States and South Korea they are estimated at 0.25% of trade value[18]. The synthesized formula for computing the portfolio value is:

$$V_i = V_{i-1}[1 + S_{i-1} * \triangle(\%)\, P_i] - C_i \tag{2.3}$$

For the computation of effective investment returns, the portfolio value function is used as a base. The weekly portfolio returns[19] are used to construct a return series. For comparison, the returns of the benchmark portfolio are also measured. They are obtained using the same testing procedure, the difference being made by the signal function, which in the case of the benchmark strategy has the following form:

$$SB_i = \begin{cases} 0, & if\ S_i = 0 \\ 1, & otherwise \end{cases} \tag{2.4}$$

Having calculated the two return functions, the final aggregated return indicators can be computed, along with the total risk and downside risk, which are then used in the calculation of the $ExM2^S$[20] estimator.

2.7. **Optimization procedure.** The optimization involved the computation of the $ExM2^S$ indicator for each pair between a trading system and a data sample for the selected testing period. The optimization is made by restricting the parameter n_2 to a maximum of 318, representing approximately 1 year and 3 months of trading, thus resulting a trading system universe of 50,086 rules. The target function is the $ExM2^S$ indicator, optimization referring to finding the combination of parameters that maximizes the target function.

In order to choose the best system from the testing period using parameter optimization, all possible combinations of trading systems are first generated (taking into consideration only the above mentioned restriction). These, in turn, are applied to the data series as per the procedure described in the previous chapter resulting a series of $ExM2^S$ estimators. The k system is chosen as being the best system in the testing period:

$$k = IndexOf(\max_{1 \le m \le M} ExM2^S_m) \tag{2.5}$$

The procedure is repeated for all issuers in the sample.

2.8. **Observations regarding the testing procedure.** The trading methodology involves some strong hypotheses, especially the one according to which $S_i < 0$, meaning there is the possibility to open short selling positions. If this hypothesis is true for the USA and Korea markets (despite the possible problems associated with finding borrowers), for Romania only recently the short sale methodology was introduced in the stock market, so the hypothesis is unreasonable in the case of local companies. In order to somewhat relax this hypothesis, a maximum leverage of 1:1 is assumed when short selling.

Another strong hypothesis is the instantaneous trading (initiating a position immediately after receiving a new trading signal). In practice, there is a need for signal confirmation, thus losing an observation from the signal occurrence. In order to mimic as close as possible the practical procedure, the trade moment is delayed by one observation from the signal occurrence. Thus, if $\Delta S_i > 0$ then we have a signal at moment i and open a position at moment $i + 1$.

The prices at which trades are made are very important for the final results. In order to avoid any possible upward bias for the $ExM2^S$ estimators, the trades are performed at the least favourable price obtained on the market in the trading period. Thus, for the buying trades it is assumed that they are done at the highest price, while for the sale trades it is

[18] This percentage is used as a reasonable estimation by Allen and Karjalainen (1999).

[19] $R_j = V_j + 1/V_{j-1}$, where $j \in (1, J)$, with J = number of weeks in the testing period and V_{j+1} is the portfolio value one week after V_j. Weekly returns were chosen because they have a high frequency, but are less volatile than daily returns. Also, discrete returns were preferred to continuous ones.

[20] Appendix 4 presents the computational method for this indicator.

assumed that they are done at the lowest price. In other words, an extra indirect trading cost is deducted from the trade individual return, i.e. the bid-ask spread. This methodology leads to the downward movement of the return estimators and, in the end, towards more prudent values that are upward bias free (although downward bias could appear). For a theoretically bias-free estimation of the excess return estimators, the trades should be performed either at the mean average price of the period, at the typical price[21], at the price representing half of the variation interval, or at the opening price, but for this study a prudent approach was preferred.

2.9. **Results confirmation procedure.** In order to evaluate the economic relevance of the selected systems, each best performing in sample system was applied to an out of sample series, thus obtaining via the same procedure an $ExM2^S{}_{os}$ estimator. For a trading system based on technical analysis indicators to be economically relevant the condition $ExM2^S{}_{os} \geq 0$ must be fulfilled, that is, the result outside the initial testing sample must be at least equal to zero. This means that the positive excess returns are consistent in time. A supplementary condition could be$ExM2^S{}_{os} \geq ExM2^S$, i.e. the out of sample results must at least equal the in sample ones.

Although this confirmation approach is the preferred one in practice, for a properly scientific confirmation it is not enough. Thus, a second test for the evaluation of the $ExM2^S$ estimators is performed. In order to statistically evaluate this indicator, its distribution must be known. Since a theoretical approach for its determination is very difficult, if not impossible, and an approach based on a Monte Carlo simulation has the inconvenience of the restrictions imposed on the initial return distribution, a methodology based on the bootstrap simulation is implemented, which has the advantage that it uses the empirical distribution of returns.

Thus, for the determination of the $ExM2^S$ empirical distribution using the bootstrap simulation, the following steps are followed:

1. The empirical distribution of the original market returns is determined.
2. 10,000 simulations for the determination of the $ExM2^S$ indicator empirical distribution (noted R) are performed. Each simulation involved passing through the following stages:

a) A simulated return series is generated using random sampling with replacement from the empirical distribution obtained in the first stage;

b) A simulated trading prices series based on the simulated return series and the first actual market price is generated;

c) The $ExM2^S$ indicator for the simulated prices series is computed using the procedure described in chapters (3.5) and (3.6).

After obtaining the empirical distributions of the $ExM2^S$ indicator, it can be established if the $ExM2^S$ estimators computed for the best in sample trading system is statistically relevant. At the same time, a statistical test can be built for the determination of the general economic relevance of the chosen system. This has the null hypothesis:

$H0 : ExM2^S > 0$ (the system is economically relevant)

$H1 : ExM2^S \leq 0$

In order to determine the dismissal or not of the null hypothesis, the probability $P1$ that the system true excess return is positive is calculated, i.e. $P1 = P(r > 0)$, where $r \in R$. The interpretation of the results is straightforward, because the bigger $P1$ is, the more economically relevant the system is, since it can obtain consistently positive results in various price evolution conditions and not only for the original price sample. $H0$ will be rejected at a confidence level of 95% if $P1 < 0.95$.

Another test is the determination of the statistical relevance of the excess return estimator. For this, the probability $P2$ for the system to obtain in any circumstances of price evolution at least the result obtained for the real trading series is computed, i.e.$P2 = P(r > ExM2^S_k)$, where $r \in R$. If $P2$ is at one extreme of the empirical distributions, the result indicator is not statistically relevant since the obtained results are hard to reproduce. The indicator is

[21] $TypicalPrice = (High + Low + Close)/3$.

statistically relevant at a confidence level of 95% if $P2 \in (0.025; 0.975)$ and at a confidence level of 90% if $P2 \in (0.05; 0.95)$. The statistical relevance of the results is tested for both in sample and out of sample estimators.

3. Results

Appendix 1 shows the centralized testing results obtained for all data samples. Table 4 shows the summarized results, where the percentages of reaching a series of objectives by the system chosen using in sample optimization are reported.

The results reported for the testing period represent the best possible results, taking into consideration the selected performance criterion ($ExM2^S$), of a "moving average cross-over" type system. These results are subject to data snooping bias, but they do not have direct monetary impact on the investor's capital, although they represent the basis for future decision making. In comparison, the results reported for the confirmation period have a potential real and direct impact on the return on investment for an investor who chooses to use this type of technical analysis system as a market investment method. In this case, the reported excess returns represent values potentially obtained by the person who would have invested in the second sub-period based on the system suggested by backtesting in the first sub-period.

The difference between the results of the two sub-samples represents an indirect measure of the magnitude of data snooping bias for the in-sample estimators. The bigger the difference between the results for the two samples is, the "luckier" the best in sample trading rule was, thus invalidating its economic value. By contrast, the closer the two results are, the more economically relevant the best in sample trading rule was. At the same time, in the latter situation, the less efficient the market is, since the information regarding the system's past profitability were not incorporated in future prices, thus allowing an investor who had this information to obtain an return on investment above the equilibrium one. The inference can more thoroughly be made via de implemented bootstrap tests.

3.1. **Profitability of technical analysis systems based on the moving average cross-over rule.** The results show an overall weak profitability of the technical analysis systems for the studied samples. As mentioned above, only the results in the confirmation period have a potential impact on the investors' portfolio. First of all it can be noted that although in around 94% of the cases the systems were capable of obtaining profits in the testing period, for the confirmation period this percentage fell to 39%. Table 5 offers additional information for this analysis, comparing the results obtained by the best performing in sample trading rule with those of the benchmark strategy, i.e. buy-and-hold. We note that even for the benchmark the success percentage dropped, but not so much.

Correlating these results with market price evolution in the two sub-samples, it can be deduced that the trading systems chosen by optimization and, implicitly, the positive results obtained in the testing period, were decisively influenced by the sustained bullish market of the testing period (2001-2005). Thus, when the market regime changed to bearish (2007-onwards), the best performing in sample systems were not able to obtain the same performances as before. Two conclusions can be extracted: firstly, the chosen systems were mostly not profitable in the confirmation period, thus generating losses to the potential investors who may have used them; and secondly, the results are decisively influenced by the specific dates used to split the samples. There are many reasons to believe that if the testing sample was chosen to overlap the remainder of the bullish market, which ended in mid to late 2007, the results would have been substantial different.

The latter conclusion has very important implications for the testing procedure since it involves taking different investment decisions only by choosing a different interval splitting date. From the practical point of view, this problem can be solved in several ways: either by using trading systems based on adaptive technical indicators which are capable to measure the market conditions and auto-adjust the parameters without external intervention, either by using extra technical or econometric models to predict the current market state and manually adjust to this, either by compressing the sub-samples in smaller time intervals (and working with more than two sub-samples) in order to bring closer as much as possible the market conditions in two consecutive sub-samples. The latter solution would also be the preferred one, given the known problems of market state prediction models.

In conclusion, given the testing results, profits generated by moving average cross-over rules chosen by in-sample optimisation tent to be inconsistent over time, which is not an attribute that a trader would want from a trading system, although this depends on the market state, a variable that a trader does not control. Thus, knowing the current market state and continuously adapting the trading strategy to it must be a constant worry in a professional's trader's activity.

Another question is if the performance of the investment portfolio exceeds the one of the benchmark portfolio, without taking into account if the systems are by their own profitable or not. The reported results regarding this question can be similarly interpreted for all types of performance indicators (columns 3-5 in Table 3 of Appendix 1 - standard and risk adjusted returns). It is noted that in the testing period only in half of the cases the chosen technical analysis strategy exceeds the benchmark, while in the confirmation period this percentage decreases to approximately one third, so that we can extract another conclusion, i.e. the trading systems based on the moving average cross-over rule were not overall capable to exceed the base profitability of the buy-and-hold benchmark strategy.

3.2. **Statistical relevance of results.** A very big difference between the statistical relevance of the in sample indicators, compared to the out of sample ones can be observed in Table 1. The percentage of the statistically relevant indicators is only 40% in the first case, while it approaches 92% in the second case.

This situation demonstrates the bias in the testing period estimators due to data snooping inherent in the procedure of choosing the best parameter combination from the universe of 50,086 possible combinations, making the in sample estimators mostly irrelevant. On the other hand, the results in the confirmation period were obtained by applying only one trading system, which mostly eliminates the possibility of data snooping bias for this sub-sample.

In other words, the results obtained in the testing period are misleading because they do not express the real performances of the chosen trading systems but only those optimized for a specific price evolution case (during the period 2001-2005), while the results in the confirmation period are significant and may have an impact on the portfolios of investors who might have used such trading systems.

Taking into consideration that the results in the confirmation period tend to be negative, we can strengthen the conclusion according to which the trading systems based on the moving average cross-over rule do not produce consistent profits for an investor who would have used them.

3.3. **Risk of technical analysis systems based on the moving average cross-over rule.** The risk indicators of the investment portfolio compared to the benchmark portfolio, both in sample and out of sample, are presented in Appendix 2. The summarized results for three representative risk indicators are presented in Table 2, i.e. *Maximum Drawdown* representative for bankruptcy risk, *Standard deviation* representative for total risk and *Semi-standard deviation* (with a threshold value of 0%) representative for downside risk.

The reported results demonstrate that using an active trading system based on the moving average cross-over rule generates lower investment risk than using the buy and hold strategy for the analysed markets. Overall, in 63% of the cases in the confirmation period (compared to 87% in the testing period) the drawdown risk was lower when using technical analysis, compared to the benchmark strategy. The percentage is better for downside risk (69% out of sample from 48% in sample), and even more so for total risk, where in almost 4/5 of the cases the implementation of technical analysis as a trading method is less risky than the benchmark passive strategy. Also, a consistent risk-reducing characteristic can be noticed, moving average crossover systems maintaining and even improving risk characteristics out of sample versus in sample: 2/3 of the cases for drawdown risk and 81% for both total risk and downside risk. So even though the systems were optimized in a bullish market, they were capable of diminishing the investment risk compared to the benchmark strategy in a strong bearish market.

The reported results are in accordance with other papers in this field[22] that sustain that using technical analysis trading system systematically generate lower risk when compared to a passive buy-and-hold strategy.

3.4. **Economic relevance of systems chosen by in-sample optimization. Differences for Romania.** The economic relevance evaluation is different from the profitability evaluation, since it is possible for a trading system to not be profitable, but still be economically relevant because it generates less risk and, thus, its risk adjusted return may be higher than that of the benchmark. In fact, this study uncovered several of these cases that will later be discussed.

Overall, the results point out a lack of relevance for the selected trading systems in the testing sample, this meaning that even the best moving average crossover rule results were not able to beat the buy and hold strategy in a strong bullish market. For the confirmation sample, approximately in one third of the cases the selected systems in the previous period are economically relevant, a fairly low percentage, allowing the extraction of the conclusion according to which the technical analysis systems based on the moving average cross-over rule are overall not economically relevant. However, some clear differences can be observed between the results when looking at individual markets. These are detailed next.

The conclusions stated so far do not support the overall usage of technical analysis trading systems based on the moving average cross-over rule. However, the evidence provides a different picture when looking only at the Romanian capital market. The reported tables show that the results obtained for here differ significantly from the ones obtained for the other two more developed markets. In fact, the overall conclusions against the usage of technical analysis presented in the previous paragraphs are mainly due to the results obtained on the external markets.

First of all, the consistence percentages on the risk reducing characteristic of technical analysis systems are 92% for maximum drawdown and 100% for the standard deviation and semi-standard deviation, compared to the external cases where the percentages range around 60%, which leads to the conclusion that, *applied to the issuers listed at the Bucharest Stock Exchange, the technical analysis systems based on the moving average cross-over rule always generate a lower investment risk when comparing it to the benchmark buy-and-hold rule.*

Secondly, the consistence percentage for out of sample adjusted excess return (Column 5 in Table 4 of Appendix 1) is almost 65%, which, even if it doesn't allow for a strong favourable conclusion, it also does not allow to disregard the possibility that technical analysis instruments are relevant and can be used for obtaining above standard returns on the Romanian market, the more since the measured excess returns increased in the confirmation period compared to the testing period, while the latter overlapped a period of great price decreases.

Finally, and most important, a clear difference between the economic relevance percentages of the systems chosen by optimization in case of Romanian issuers, compared to the issuers from the two external markets (Column 7 in Table 4 of Appendix 1) can be observed. An economically relevant trading system could be found for more than half of the most important companies listed on the Bucharest Stock Exchange. This is very important as it demonstrates that the local stock market is not overall informationally efficient. Also, the difference compared to the values for the external markets is significant, so that it may also be stated that there is a strong relative efficiency difference between the Romanian stock market and the two external ones, in the favour of the latter ones. This result is very interesting and its causes need more investigation, although it can be linked to the market development state.

[22]Park and Irwin (2007) give several examples of such papers.

In conclusion, we observe a different situation when looking at the results for Romania compared to the other two studied markets, this leading us to believe that the Romanian stock market is, on one hand, not overall informationally efficient and, on another hand, less efficient that the stock markets in South Korea and the United States. The reported results contradict the conclusion of a week form efficient market reported by Dragotă, Stoian, Pele, Mitrică and Bensafta (2009) for the Romanian stock market and support the relative market efficiency concept of Hsu and Kuan (2005), although a relationship with the degree of market maturity or any other independent variable is not investigated.

3.5. **Personal considerations.** The methodology implemented hear comes with some advantages that reinforce the validity of the stated conclusions: (1) the testing method mimic very closely the process implemented by stock market professionals, i.e. in sample optimization is used to select a trading system that is later used in the investment decision process (in our case, is tested out of sample for economical relevance); (2) the results are adjusted for trading costs and risk; (3) a prudent approach is implemented, one that is not common in international literature, in the sense that the least favourable prices are used in simulating the trading activity (the high price for buy trades and the low price for sell trades), thus incorporating an extra trading costs in the analysis and downward shifting the excess return values, hopefully providing biased-free estimators.

But there are also some pitfalls attached: (1) a small universe of trading rules is used, i.e. the one derived from using only the "moving average cross-over" rule, with a maximum period parameter of 318. In reality, the arsenal of trading indicators used by technical analysts is much larger and future investigations of different technical analysis methods should be conducted for the Romanian stock market; (2) a relatively small number of issuers are used in testing. Even so, these samples produced 535 trades for the best performing trading rules, out of which 396 in the confirmation period, validating the conclusions for the tested issuers, but disallowing the generalization of these conclusions for the entire markets. However, in the case of the Romanian market the number of issuers included in the tests is very difficult to increase due to liquidity constraints which make the application of technical analysis methods irrelevant. This, together with the fact that the selected issuers make for more than 80% on total stock market value, allow the generalization of the conclusions for the local market; (3) the implementation of short selling trades in the case of Romanian listed companies is a hypothesis hard to sustain by practical reality. This however, does not necessarily dismiss the conclusions for the local market given that short trades tend not to be consistently profitable. This was uncovered by the author in subsequent testing that is not reported in this paper and will be detailed in subsequent studies.

On the other hand, a few problems were noted while conducting the research that this paper is based on, while trying to implement a methodology that is both scientifically and practically relevant. Several important papers, out of which we may point out to Sullivan, Timmermann and White (1999) and Timmermann and Granger (2004), have promoted the usage of a complete universe of technical trading rules when testing, in order to quantify as accurately as possible the bias in estimator values caused by data snooping. However, two inconsistencies of using a complete universe in testing were uncovered, that make applying this idea both theoretically inaccurate and unpractical for professional traders:

Firstly, the studies which researched the investors' attitude towards technical analysis (ex. Menkhoff, 2010) showed that this investment method is used for decisions up to 6 months. Often, the reported interval was less, but the maximum is fixed at 6 months. However, within the optimization operations, by using a complete universe of rules, in almost all cases of this paper's testing results the parameters of the best performing trading rules surpassed this limit[23].

[23] Please note the column „Best system IN SAMPLE" in Appendix 1. This study tried to minimize this inconsistency by limiting parameter n2 to a maximum of 318, representing roughly 1 and $\frac{1}{4}$ years, this also serving for increasing computational efficiency.

Therefore we have an inconsistency between current theory and empirical evidence regarding investor behaviour. Would a technical analyst use trading systems with an investment horizon far above he's own only because the results in backtesting were better? And what would his answer be if he would know that the choice of the best performing in sample system is very sensitive to the data splitting operation (as this paper and others point out)? Although the answer cannot be exactly determined, it is more probable that he would not implement the suggested system, because of the uncertainties generated by using an unknown investment method. These observations lead to the recommendation that a limited and more realistic universe of trading rules should be used in testing[24]. To the two above arguments we may add a third technological one, i.e. restricting the universe of rules leads to an increase of testing performance and a decrease in research cost, this being highly appreciated by any investor, especially a retail one, that does not have sufficient capital to invest in state of the art hardware that can handle the vast amount of computations.

Secondly, many of the rules chosen following optimization do not make any sense for a professional investor. Professionals explain that technical analysis is based on certain theoretical concepts, and some of these concepts are taken from economic sciences, empirical reality and psychology[25]. However, for example, in the case of SIF1 the optimization procedure chose the $EMA(2) > SMA(315)$ trading rule. Appendix 3 presents a chart of portfolio values for this case (the investment portfolio, the benchmark portfolio and the risk free portfolio) in the testing and confirmation periods. A clear case of data snooping bias can be observed simply by noticing that this rule generated only one trade in the testing period[26], i.e. a buy trade at the most favourable point in time for the first sub-sample. In other words, within the optimization procedure, a trading system that bought at the minimum and sold at the maximum was chosen, thus generating the perfect trade for the studied interval. This idea is absurd and would be strongly contested even by the most novice investor, but otherwise makes no difference to the computer. No practitioner would use such a system, risking his capital in the process.

Through these two observations, the author encourages the usage of a limited universe of trading rules by referring to technical analysis theory and the empirical evidences regarding the behaviour of investors who apply methods specific to technical analysis, as opposed to utilizing a complete universe of trading rules that is both in some cases irrelevant and computational expensive.

4. Conclusions

This paper reports the results of a first study of the relevance of technical analysis instruments for the investment process on the Romanian stock market (Bucharest Stock Exchange). A standard testing method is implemented in which the data is divided into two samples, a universe of trading systems based on the moving average crossover rule is constructed, the systems are tested on the first sample and the best performing one is selected for future trading. The results are confirmed using out of sample trading and econometric tests based on the bootstrap simulation. Trading system performance is measured via the geometric M2 for Sortino excess return (denoted $ExM2^S$) indicator that reports geometric excess return adjusted to trading cost and downside risk. For comparison, data samples from issuers listed on NYSE in the United States of America and KRX in South Korea are also tested. Finally, implications of testing results regarding Romanian market efficiency are drawn.

[24]In case the investor takes decisions on a larger investment horizon, for instance 100-300 days, the universe of rules should contain only those rules referring to this period, i.e. between 100 and 300. In case the investor aims a period of up to 6 weeks, then the parameters must be limited to 30. This is applicable for all trading systems that rely on time-based parameters.

[25]For example, investment cycles, economic trends, speculative bubbles, price over and under-reaction, etc.

[26]This can be found in appendix 1, table „Indicators detailing the behavior of the best performing trading system", column „Number of trades", line "RO_SIF1".

The paper reports an overall lack of profitability and a lack of economic relevance for the considered systems, but good results for the Romanian market by comparison with the two external markets. Since for more than half of tested issuers on the Romanian stock market an economically relevant trading system could be found, the conclusion that the local market is not overall informationally efficient can be drawn. Also, the results support the relative market efficiency concept of Hsu and Kuan (2005).

On the other hand, the technical analysis trading systems based on the moving average crossover rule do a great job at lowering investment risk for traders that use them, in all considered situations.

The reported conclusions are reinforced by the fact that the testing method mimicked very closely the process implemented by stock market professionals, the results are adjusted for trading costs and risk and a prudent approach is implemented, in the sense that the least favourable prices are used in simulating the trading activity (the high price for buy trades and the low price for sell trades), thus incorporating an extra bid-ask spread trading costs and diminishing the bias in the excess return estimators. On the other hand, improvements can be made by using a larger universe of trading rules, incorporating more issuers into testing and eliminating the short selling hypothesis for markets in which it is not applicable.

Finally, some observations regarding the optimization procedure as well as the obvious discrepancies between the theoretical testing approach suggested by Sullivan, Timmermann and White (1999) or Timmermann and Granger (2004) and the practical investor behaviour highlighted by Menkhoff (2010) leads to the recommendation that a limited and more realistic universe of trading rules should be used in testing technical analysis methods.

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Appendix 1. Testing results

Table 1: Indicators detailing the behavior of the best performing trading system

Details		In sample				
Issuer symbol	Rule of best performing trading system	Number of trades	Percentage of profitable trades	Max. no. of consecutive losing trades	Avg. length of winning trades	Avg. length of loosing trades
1	2	3	4	5	6	7
KO_000270	EMA(147) > SMA(181)	4	0,75	1	280 days	167 days
KO_003600	EMA(130) > SMA(153)	5	0,8	1	243 days	78 days
KO_005380	EMA(52) > SMA(280)	1	1	0	876 days	0
KO_005490	EMA(78) > SMA(262)	1	1	0	903 days	0
KO_005930	EMA(155) > SMA(169)	4	1	0	258 days	0
KO_012330	EMA(181) > SMA(207)	5	0,6	1	293 days	199 days
KO_051910	EMA(69) > SMA(314)	2	0,5	1	370 days	693 days
KO_053000	EMA(72) > SMA(303)	1	1	0	903 days	0
KO_055550	EMA(2) > SMA(291)	1	1	0	529 days	0
KO_066570	EMA(49) > SMA(307)	3	0,6667	1	414 days	94 days
RO_ALR	EMA(218) > SMA(243)	2	1	0	599 days	0
RO_ATB	EMA(150) > SMA(153)	5	0,6	1	392 days	102 days
RO_AZO	EMA(2) > SMA(254)	2	0,5	1	740 days	45 days
RO_BCC	EMA(50) > SMA(109)	5	0,4	3	272 days	134 days
RO_BIO	EMA(223) > SMA(260)	3	0,3333	2	219 days	461 days
RO_BRD	EMA(77) > SMA(168)	3	0,6667	1	445 days	532 days
RO_BRK	EMA(8) > SMA(23)	26	0,4231	5	63 days	19 days
RO_OIL	EMA(229) > SMA(283)	2	0,5	1	1057 days	45 days

Details		In sample				
Issuer symbol	Rule of best performing trading system	Number of trades	Percentage of profitable trades	Max. no. of consecutive losing trades	Avg. length of winning trades	Avg. length of loosing trades
1	2	3	4	5	6	7
RO_OLT	EMA(127) > SMA(310)	2	0,5	1	1176 days	3 days
RO_RRC	EMA(256) > SMA(295)	3	1	0	214 days	0
RO_SIF1	EMA(155) > SMA(242)	3	1	0	413 days	0
RO_SIF2	EMA(51) > SMA(216)	3	0,6667	1	590 days	110 days
RO_SIF3	EMA(138) > SMA(206)	3	1	0	437 days	0
RO_SIF4	EMA(125) > SMA(200)	3	1	0	441 days	0
RO_SIF5	EMA(106) > SMA(221)	3	0,6667	1	580 days	124 days
RO_SNP	EMA(216) > SMA(284)	3	1	0	359 days	0
RO_TEL	EMA(47) > SMA(97)	2	1	0	304 days	0
US_BAC	EMA(39) > SMA(317)	1	1	0	1120 days	0
US_GE	EMA(232) > SMA(245)	2	1	0	613 days	0
US_IBM	EMA(294) > SMA(298)	3	1	0	382 days	0
US_JNJ	EMA(297) > SMA(301)	3	0,6667	1	527 days	89 days
US_JPM	EMA(96) > SMA(168)	7	0,4286	3	331 days	87 days
US_KO	EMA(161) > SMA(164)	5	1	0	269 days	0
US_PG	EMA(232) > SMA(236)	4	0,75	1	346 days	200 days
US_T	EMA(225) > SMA(242)	3	0,6667	1	589 days	53 days
US_WMT	EMA(302) > SMA(303)	4	0,25	3	353 days	262 days
US_XOM	EMA(164) > SMA(307)	2	1	0	567 days	0

Details		Out of sample				
Issuer symbol	Rule of best performing trading system	Number of trades	Percentage of profitable trades	Max. no. of consecutive losing trades	Avg. length of winning trades	Avg. length of loosing trades
1	2	8	9	10	11	12
KO_000270	EMA(147) > SMA(181)	7	0,2857	4	617 days	146 days
KO_003600	EMA(130) > SMA(153)	10	0,4	4	300 days	125 days
KO_005380	EMA(52) > SMA(280)	8	0,125	7	886 days	153 days
KO_005490	EMA(78) > SMA(262)	4	1	0	488 days	0
KO_005930	EMA(155) > SMA(169)	11	0,1818	6	269 days	157 days
KO_012330	EMA(181) > SMA(207)	12	0,25	7	386 days	136 days
KO_051910	EMA(69) > SMA(314)	7	0,2857	3	756 days	165 days
KO_053000	EMA(72) > SMA(303)	4	0,75	1	566 days	389 days
KO_055550	EMA(2) > SMA(291)	20	0,1	11	423 days	34 days
KO_066570	EMA(49) > SMA(307)	12	0,1667	8	341 days	144 days
RO_ALR	EMA(218) > SMA(243)	6	0,5	2	538 days	207 days
RO_ATB	EMA(150) > SMA(153)	11	0,4545	4	312 days	126 days
RO_AZO	EMA(2) > SMA(254)	18	0,1111	13	472 days	46 days
RO_BCC	EMA(50) > SMA(109)	13	0,2308	7	437 days	27 days
RO_BIO	EMA(223) > SMA(260)	8	0,25	4	407 days	214 days
RO_BRD	EMA(77) > SMA(168)	8	0,5	3	419 days	145 days
RO_BRK	EMA(8) > SMA(23)	42	0,2857	7	74 days	18 days
RO_OIL	EMA(229) > SMA(283)	9	0,2222	4	453 days	182 days

Details		Out of sample				
Issuer symbol	Rule of best performing trading system	Number of trades	Percentage of profitable trades	Max. no. of consecutive losing trades	Avg. length of winning trades	Avg. length of loosing trades
1	2	8	9	10	11	12
RO_OLT	EMA(127) > SMA(310)	7	0,5714	2	440 days	167 days
RO_RRC	EMA(256) > SMA(295)	4	0,75	1	451 days	292 days
RO_SIF1	EMA(155) > SMA(242)	8	0,375	3	458 days	192 days
RO_SIF2	EMA(51) > SMA(216)	8	0,625	2	360 days	179 days
RO_SIF3	EMA(138) > SMA(206)	8	0,75	1	344 days	135 days
RO_SIF4	EMA(125) > SMA(200)	8	0,375	4	449 days	196 days
RO_SIF5	EMA(106) > SMA(221)	8	0,5	3	459 days	125 days
RO_SNP	EMA(216) > SMA(284)	6	0,6667	1	509 days	49 days
RO_TEL	EMA(47) > SMA(97)	9	0,2222	5	183 days	108 days
US_BAC	EMA(39) > SMA(317)	8	0,375	2	587 days	120 days
US_GE	EMA(232) > SMA(245)	10	0,2	5	465 days	179 days
US_IBM	EMA(294) > SMA(298)	12	0,25	5	364 days	141 days
US_JNJ	EMA(297) > SMA(301)	9	0	9	0	263 days
US_JPM	EMA(96) > SMA(168)	11	0,2727	4	343 days	167 days
US_KO	EMA(161) > SMA(164)	8	0,5	2	406 days	185 days
US_PG	EMA(232) > SMA(236)	13	0,1538	8	410 days	140 days
US_T	EMA(225) > SMA(242)	7	0,5714	1	512 days	106 days
US_WMT	EMA(302) > SMA(303)	11	0	11	0	215 days
US_XOM	EMA(164) > SMA(307)	5	0,4	3	749 days	289 days

Table 2: In sample return indicators

Symbol	Rule of best performing trading system	Total return	Total geometric excess return	Sharpe ratio	M2 return	Geometric excess M2 return
1	2	3	4	5	6	7
KO_000270	EMA(147) > SMA(181)	1,5625	0,3929	26,8069	1,5764	0,4004
KO_003600	EMA(130) > SMA(153)	3,0386	-0,1554	38,0439	3,0708	-0,1487
KO_005380	EMA(52) > SMA(280)	0,426	-0,0148	4,9201	0,4288	-0,0128
KO_005490	EMA(78) > SMA(262)	0,4102	-0,0354	4,6706	0,4121	-0,0341
KO_005930	EMA(155) > SMA(169)	0,9606	0,4862	19,1429	1,0225	0,5331
KO_012330	EMA(181) > SMA(207)	3,2304	1,6333	42,3967	3,62	1,8758
KO_051910	EMA(69) > SMA(314)	0,0029	0,1497	-4,5678	-0,0059	0,1396
KO_053000	EMA(72) > SMA(303)	1,4586	-0,0368	21,5856	1,4703	-0,0322
KO_055550	EMA(2) > SMA(291)	0,0672	-0,0393	-2,0632	0,066	-0,0404
KO_066570	EMA(49) > SMA(307)	0,1941	-0,3633	-0,4836	0,1948	-0,363
RO_ALR	EMA(218) > SMA(243)	9,0223	0,7982	60,5485	9,2022	0,8305
RO_ATB	EMA(150) > SMA(153)	5,8168	0,5388	83,7068	6,2756	0,6424
RO_AZO	EMA(2) > SMA(254)	-0,108	1,7391	-9,917	-0,4052	0,8266
RO_BCC	EMA(50) > SMA(109)	0,3265	0,9976	0,2635	0,3297	1,0025
RO_BIO	EMA(223) > SMA(260)	-0,0332	-0,4971	-0,3945	0,0705	-0,4432
RO_BRD	EMA(77) > SMA(168)	5,516	0,0909	40,2561	5,5546	0,0973
RO_BRK	EMA(8) > SMA(23)	1,9467	4,7111	21,4185	2,0632	4,9367
RO_OIL	EMA(229) > SMA(283)	2,2934	0,021	9,21	2,2997	0,0229

Symbol	Rule of best performing trading system	Sortino ratio	Sortino M2 return	Geometric M2 for Sortino excess return	P1	P2
1	2	8	9	10	11	12
KO_000270	EMA(147) > SMA(181)	0,04372	1,5787	0,4016	0,0372	0,0073
KO_003600	EMA(130) > SMA(153)	0,07118	2,9652	-0,1708	0,0011	0,0048
KO_005380	EMA(52) > SMA(280)	7,23	0,4284	-0,0131*	0,0784	0,0867
KO_005490	EMA(78) > SMA(262)	6,68	0,412	-0,0342*	0,0482	0,0821
KO_005930	EMA(155) > SMA(169)	0,02901	1,0708	0,5697	0,0690	0,0011
KO_012330	EMA(181) > SMA(207)	0,09089	5,8668	3,2743	0,1961	0,0219
KO_051910	EMA(69) > SMA(314)	-6,34	0,0112	0,1592*	0,2400	0,1697
KO_053000	EMA(72) > SMA(303)	0,03173	1,4698	-0,0324*	0,0382	0,0496
KO_055550	EMA(2) > SMA(291)	-2,9	0,0682	-0,0384*	0,0851	0,1037
KO_066570	EMA(49) > SMA(307)	-0,71	0,1915	-0,3647*	0,0312	0,2204
RO_ALR	EMA(218) > SMA(243)	0,11684	9,4219	0,8699	0,0538	0,0042
RO_ATB	EMA(150) > SMA(153)	0,14394	8,1067	1,0557	0,0048	0,0000
RO_AZO	EMA(2) > SMA(254)	-0,01208	0,1421	2,5071*	0,2377	0,0628
RO_BCC	EMA(50) > SMA(109)	0,52	0,3428	1,0221*	0,4721	0,1275
RO_BIO	EMA(223) > SMA(260)	-0,7	-0,1247	-0,5447*	0,1263	0,3991
RO_BRD	EMA(77) > SMA(168)	0,09645	5,5731	0,1004	0,0216	0,0186
RO_BRK	EMA(8) > SMA(23)	0,04681	3,5202	7,7606	0,0440	0,0000
RO_OIL	EMA(229) > SMA(283)	8,36	2,2967	0,022*	0,0750	0,0689

Symbol	Rule of best performing trading system	Total return	Total geometric excess return	Sharpe ratio	M2 return	Geometric excess M2 return
1	2	3	4	5	6	7
RO_OLT	EMA(127) > SMA(310)	2,7373	-0,0162	6,4257	2,7489	-0,0131
RO_RRC	EMA(256) > SMA(295)	0,5374	0,4627	4,7086	0,6112	0,5329
RO_SIF1	EMA(155) > SMA(242)	10,9596	-0,0476	139,8647	10,9507	-0,0484
RO_SIF2	EMA(51) > SMA(216)	9,2878	-0,0677	106,3872	9,324	-0,0644
RO_SIF3	EMA(138) > SMA(206)	10,322	-0,0121	143,0429	10,3961	-0,0056
RO_SIF4	EMA(125) > SMA(200)	11,1461	-0,0178	133,6889	11,1757	-0,0154
RO_SIF5	EMA(106) > SMA(221)	9,568	-0,0415	100,7532	9,6198	-0,0368
RO_SNP	EMA(216) > SMA(284)	2,5508	-0,0005	25,3704	2,5579	0,0015
RO_TEL	EMA(47) > SMA(97)	0,9523	3,359	26,4696	1,5362	4,6628
US_BAC	EMA(39) > SMA(317)	0,4194	-0,0172	10,1166	0,4234	-0,0145
US_GE	EMA(232) > SMA(245)	1,1118	1,246	35,8542	1,6272	1,7941
US_IBM	EMA(294) > SMA(298)	0,3633	0,9137	8,8494	0,4736	1,0685
US_JNJ	EMA(297) > SMA(301)	0,2333	0,1178	5,7396	0,2651	0,1466
US_JPM	EMA(96) > SMA(168)	0,8366	0,7515	18,3395	1,1143	1,0163
US_KO	EMA(161) > SMA(164)	0,4966	0,5505	14,1158	0,5398	0,5953
US_PG	EMA(232) > SMA(236)	0,2677	-0,1235	7,8844	0,271	-0,1212
US_T	EMA(225) > SMA(242)	0,8038	1,582	20,5187	1,0896	1,9911
US_WMT	EMA(302) > SMA(303)	-0,094	0,1373	-6,354	-0,1121	0,1146
US_XOM	EMA(164) > SMA(307)	0,8102	0,2871	28,2125	1,0241	0,4393

Symbol	Rule of best performing trading system	Sortino ratio	Sortino M2 return	Geometric M2 for Sortino excess return	P1	P2
1	2	8	9	10	11	12
RO_OLT	EMA(127) > SMA(310)	0,01353	2,7431	-0,0146*	0,1093	0,1262
RO_RRC	EMA(256) > SMA(295)	6,76	0,6386	0,559	0,2197	0,0109
RO_SIF1	EMA(155) > SMA(242)	0,20016	10,8832	-0,0537	0,0038	0,0066
RO_SIF2	EMA(51) > SMA(216)	0,17757	9,276	-0,0688	0,0036	0,0061
RO_SIF3	EMA(138) > SMA(206)	0,20818	10,2249	-0,0206	0,0032	0,0034
RO_SIF4	EMA(125) > SMA(200)	0,21224	11,1555	-0,017	0,0023	0,0024
RO_SIF5	EMA(106) > SMA(221)	0,16916	9,5489	-0,0432	0,0171	0,0211
RO_SNP	EMA(216) > SMA(284)	0,02556	2,5538	0,0004*	0,0317	0,0317
RO_TEL	EMA(47) > SMA(97)	0,05038	2,1677	6,0728	0,4540	0,0009
US_BAC	EMA(39) > SMA(317)	0,01407	0,4232	-0,0146	0,0193	0,0196
US_GE	EMA(232) > SMA(245)	0,05838	1,7222	1,8952	0,2645	0,0000
US_IBM	EMA(294) > SMA(298)	0,01405	0,5242	1,1395*	0,4400	0,0284
US_JNJ	EMA(297) > SMA(301)	8,19	0,2574	0,1396*	0,1539	0,0449
US_JPM	EMA(96) > SMA(168)	0,0295	1,2621	1,1573	0,2213	0,0065
US_KO	EMA(161) > SMA(164)	0,02128	0,5918	0,6492	0,1702	0,0018
US_PG	EMA(232) > SMA(236)	0,01161	0,2638	-0,1262	0,0001	0,0016
US_T	EMA(225) > SMA(242)	0,03556	1,3198	2,3207	0,3494	0,0003
US_WMT	EMA(302) > SMA(303)	-8,68	-0,084	0,1498*	0,3716	0,2634
US_XOM	EMA(164) > SMA(307)	0,04501	1,1138	0,503	0,1053	0,0076

* Statistically relevant

Table 3: Out of sample return indicators

Symbol	Rule of best performing trading system	Total return	Total geometric excess return	Sharpe ratio	M2 return	Geometric excess M2 return
1	2	3	4	5	6	7
KO_000270	EMA(147) > SMA(181)	-0,3186	-0,8556	-10,1198	-0,3263	-0,8573
KO_003600	EMA(130) > SMA(153)	0,7552	-0,3418	6,4563	0,7895	-0,3289
KO_005380	EMA(52) > SMA(280)	0,0021	-0,688	-6,6289	-0,0227	-0,6958
KO_005490	EMA(78) > SMA(262)	1,3116	0,4075	19,3802	1,3712	0,4438
KO_005930	EMA(155) > SMA(169)	-0,7093	-0,8327	-24,9211	-0,7169	-0,8371
KO_012330	EMA(181) > SMA(207)	-0,9364	-0,9872	-23,9538	-0,8444	-0,9687
KO_051910	EMA(69) > SMA(314)	-0,7387	-0,9764	-15,8163	-0,5723	-0,9614
KO_053000	EMA(72) > SMA(303)	0,2915	1,2329	-1,5637	0,2632	1,1839
KO_055550	EMA(2) > SMA(291)	-0,8001	-0,738	-19,4046	-0,8329	-0,7811
KO_066570	EMA(49) > SMA(307)	-0,8907	-0,8744	-21,0984	-0,8524	-0,8304
RO_ALR	EMA(218) > SMA(243)	0,0965	-0,0809	-6,6088	-0,0234	-0,1814
RO_ATB	EMA(150) > SMA(153)	-0,0193	0,588	-13,1066	-0,1562	0,3664
RO_AZO	EMA(2) > SMA(254)	-0,1614	-0,8253	-6,2204	-0,2395	-0,8416
RO_BCC	EMA(50) > SMA(109)	-0,2294	6,8772	-17,6883	-0,7924	1,1225
RO_BIO	EMA(223) > SMA(260)	-0,5224	0,3959	-11,6699	-0,8074	-0,4371
RO_BRD	EMA(77) > SMA(168)	0,5416	0,5773	8,7149	0,6969	0,7363
RO_BRK	EMA(8) > SMA(23)	-0,4919	9,4508	-7,3812	-0,697	5,2335
RO_OIL	EMA(229) > SMA(283)	-0,5112	-0,2951	-13,9899	-0,5805	-0,3951

Symbol	Rule of best performing trading system	Sortino ratio	Sortino M2 return	Geometric M2 for Sortino excess return	P1	P2
1	2	8	9	10	11	12
KO_000270	EMA(147) > SMA(181)	-0,01386	-0,3579	-0,864*	0,0071	0,2438
KO_003600	EMA(130) > SMA(153)	0,01003	0,7714	-0,3357*	0,0109	0,0384
KO_005380	EMA(52) > SMA(280)	-9,54	0,0139	-0,6844*	0,0285	0,4174
KO_005490	EMA(78) > SMA(262)	0,02971	1,4222	0,4748*	0,1121	0,0260
KO_005930	EMA(155) > SMA(169)	-0,0323	-0,8112	-0,8914*	0,0081	0,3845
KO_012330	EMA(181) > SMA(207)	-0,0295	-1,29	-1,0583*	0,0006	0,5416
KO_051910	EMA(69) > SMA(314)	-0,01956	-1,1839	-1,0166*	0,0168	0,5736
KO_053000	EMA(72) > SMA(303)	-2,35	0,3233	1,2878*	0,3147	0,1694
KO_055550	EMA(2) > SMA(291)	-0,02336	-0,9375	-0,9181*	0,0575	0,2031
KO_066570	EMA(49) > SMA(307)	-0,02744	-1,0107	-1,0122*	0,2235	0,4693
RO_ALR	EMA(218) > SMA(243)	-0,01034	0,1825	-0,0088*	0,2358	0,2369
RO_ATB	EMA(150) > SMA(153)	-0,02001	0,2172	0,971*	0,1389	0,0929
RO_AZO	EMA(2) > SMA(254)	-0,011	-0,1318	-0,8191*	0,0034	0,1225
RO_BCC	EMA(50) > SMA(109)	-0,02467	0,3769	13,0753*	0,5817	0,2065
RO_BIO	EMA(223) > SMA(260)	-0,01576	-0,2718	1,1282*	0,3498	0,2763
RO_BRD	EMA(77) > SMA(168)	0,01307	0,6961	0,7354*	0,2051	0,0471
RO_BRK	EMA(8) > SMA(23)	-0,01252	-0,2591	14,2407	0,0170	0,0086
RO_OIL	EMA(229) > SMA(283)	-0,02118	-0,5034	-0,2838*	0,2903	0,3128

Symbol	Rule of best performing trading system	Total return	Total geometric excess return	Sharpe ratio	M2 return	Geometric excess M2 return
1	2	3	4	5	6	7
RO_OLT	EMA(127) > SMA(310)	0,8695	-0,629	2,2321	0,8906	-0,6248
RO_RRC	EMA(256) > SMA(295)	0,7577	2,6741	5,988	0,8991	2,9695
RO_SIF1	EMA(155) > SMA(242)	0,09	0,8314	-9,9976	-0,1321	0,4581
RO_SIF2	EMA(51) > SMA(216)	-0,5198	-0,3914	-18,4682	-0,839	-0,796
RO_SIF3	EMA(138) > SMA(206)	0,4344	1,0506	-3,4996	0,3812	0,9746
RO_SIF4	EMA(125) > SMA(200)	-0,0075	0,6866	-12,1432	-0,1851	0,3848
RO_SIF5	EMA(106) > SMA(221)	1,1002	1,7546	7,7519	1,2897	2,0031
RO_SNP	EMA(216) > SMA(284)	0,4256	1,1257	-3,375	0,3497	1,0126
RO_TEL	EMA(47) > SMA(97)	-0,3085	-0,3362	-10,2414	-0,3379	-0,3644
US_BAC	EMA(39) > SMA(317)	0,185	6,3009	1,6154	0,2711	6,8312
US_GE	EMA(232) > SMA(245)	-0,4286	0,0427	-15,1542	-0,5898	-0,2515
US_IBM	EMA(294) > SMA(298)	-0,5348	-0,8254	-21,8687	-0,5368	-0,8262
US_JNJ	EMA(297) > SMA(301)	-0,564	-0,607	-32,9946	-0,5551	-0,599
US_JPM	EMA(96) > SMA(168)	-0,4578	-0,4871	-12,5077	-0,591	-0,6131
US_KO	EMA(161) > SMA(164)	0,7627	-0,0229	29,8058	0,8162	0,0067
US_PG	EMA(232) > SMA(236)	-0,5643	-0,6746	-32,6834	-0,5623	-0,6732
US_T	EMA(225) > SMA(242)	0,8065	0,0604	26,1035	0,8586	0,091
US_WMT	EMA(302) > SMA(303)	-0,6444	-0,7229	-29,253	-0,5971	-0,686
US_XOM	EMA(164) > SMA(307)	0,1834	-0,2064	2,2264	0,1857	-0,2048

Symbol	Rule of best performing trading system	Sortino ratio	Sortino M2 return	Geometric M2 for Sortino excess return	P1	P2
1	2	8	9	10	11	12
RO_OLT	EMA(127) > SMA(310)	4,3	0,876	-0,6277*	0,1010	0,2876
RO_RRC	EMA(256) > SMA(295)	9,54	0,9179	3,0088*	0,3498	0,0882
RO_SIF1	EMA(155) > SMA(242)	-0,01431	0,2991	1,1826*	0,2146	0,1498
RO_SIF2	EMA(51) > SMA(216)	-0,0251	-0,3167	-0,1339*	0,1869	0,1970
RO_SIF3	EMA(138) > SMA(206)	-4,98	0,4987	1,1426*	0,1950	0,1425
RO_SIF4	EMA(125) > SMA(200)	-0,01698	0,1832	1,0106*	0,1733	0,1162
RO_SIF5	EMA(106) > SMA(221)	0,01127	1,2708	1,9783*	0,2004	0,0746
RO_SNP	EMA(216) > SMA(284)	-5,01	0,5117	1,2541*	0,2500	0,1300
RO_TEL	EMA(47) > SMA(97)	-0,01456	-0,2528	-0,2828*	0,1364	0,1926
US_BAC	EMA(39) > SMA(317)	2,35	0,2617	6,7731*	0,5189	0,1691
US_GE	EMA(232) > SMA(245)	-0,02191	-0,2301	0,4051*	0,3141	0,2617
US_IBM	EMA(294) > SMA(298)	-0,02942	-0,5995	-0,8497*	0,0000	0,4258
US_JNJ	EMA(297) > SMA(301)	-0,04149	-0,6186	-0,6562*	0,1276	0,5559
US_JPM	EMA(96) > SMA(168)	-0,01724	-0,4306	-0,4613*	0,1255	0,2259
US_KO	EMA(161) > SMA(164)	0,04653	0,886	0,0454	0,0000	0,0000
US_PG	EMA(232) > SMA(236)	-0,04267	-0,6173	-0,7143*	0,0025	0,4353
US_T	EMA(225) > SMA(242)	0,03841	0,8486	0,0851	0,0007	0,0001
US_WMT	EMA(302) > SMA(303)	-0,03757	-0,775	-0,8247*	0,0042	0,6361
US_XOM	EMA(164) > SMA(307)	3,18	0,1883	-0,2031*	0,0183	0,1135

* Statistically relevant

Tabel 4: Results obtained by the best performing in sample system

1	2	3	4	5	6	7
South Korea	40.00%	60.00%	0.00%	20.00%	100.00%	20.00%
Romania	58.82%	35.29%	0.00%	64.71%	94.12%	52.94%
United States	80.00%	30.00%	0.00%	40.00%	80.00%	10.00%
TOTAL	59.46%	40.54%	0.00%	45.95%	91.89%	32.43%

*Column 2: percentage of issuers for which the best performing in sample system brought economic excess returns during the testing period (ExM2S > 0),
*Column 3: percentage of issuers for which the excess return estimator in the testing period is statistically relevant (P2 > 0,025 and P2 < 0,975),
*Column 4: percentage of issuers for which the best performing in sample system has an economic relevance (P1 < 0,95),
*Column 5: percentage of issuers for which the best performing in sample system obtained economic excess returns in the confirmation period (ExM2SOS > 0),
*Column 6: percentage of issuers for which the excess return estimator in the confirmation period is statistically relevant (P2OS > 0,025 and P2OS < 0,975),
*Column 7: percentage of issuers for which the system is economically relevant in the confirmation period. For a system to be economically relevant in the confirmation period, three conditions must be met simultaneously: the excess return estimator must be positive (ExM2SOS > 0) and statistically relevant (P2OS > 0,05 and P2OS < 0,95), and it has to at least equal the one obtained in the testing sample (ExM2SOS > ExM2S)[27].

Tabel 5: Obtaining positive returns.
Trading system performance vs. Benchmark performance

Strategy	Testing period	Confirmation period
Trading system	93.94%	39.39%
Benchmark	78.79%	54.55%

[27]Please note that the $P1$ probability is not used in this inference, as the author does not support the idea that the results of a given trading system must be space consistent in order for it to be considered economically relevant for a certain asset. The obtained P1 values are reported in the appendix to help the readers make their own critical analysis.

Appendix 2. Risk indicators of best performing trading rule and buy-and-hold rule reported both in and out of sample

Table 1: Risk indicators of best performing trading rule and buy-and-hold rule

Details		In sample results			Out of sample results		
Symbol	Element	MDD*	SD**	SSD***	MDD*	SD**	SSD***
RO.ATB	Portfolio	-0.3690	0.0498	0.0290	-0.6428	0.0502	0.0328
	Benchmark	-0.3724	0.0547	0.0441	-0.8409	0.0602	0.0444
RO.AZO	Portfolio	-0.5706	0.0794	0.0567	-0.9476	0.0848	0.0536
	Benchmark	-0.6140	0.0797	0.0543	-0.8520	0.0998	0.0538
RO.BIO	Portfolio	-0.9266	0.1056	0.0811	-0.5323	0.0533	0.0363
	Benchmark	-0.7625	0.0864	0.0708	-0.9400	0.0768	0.0555
RO.BRD	Portfolio	-0.4703	0.1391	0.0667	-0.7708	0.0474	0.0347
	Benchmark	-0.4823	0.1395	0.0674	-0.8744	0.0613	0.0417
RO.OLT	Portfolio	-0.5377	0.1492	0.0788	-0.7665	0.1084	0.0566
	Benchmark	-0.5377	0.1491	0.0741	-0.9186	0.1200	0.0583
RO.RRC	Portfolio	-0.3906	0.0500	0.0403	-0.5274	0.0557	0.0351
	Benchmark	-0.5079	0.0585	0.0457	-0.8794	0.0768	0.0503
RO.SIF1	Portfolio	-0.3941	0.0576	0.0544	-0.8826	0.0566	0.0440
	Benchmark	-0.3941	0.0572	0.0533	-0.9167	0.0759	0.0528
RO.SIF2	Portfolio	-0.4147	0.0691	0.0610	-0.8395	0.0592	0.0452
	Benchmark	-0.4147	0.0690	0.0604	-0.9335	0.0769	0.0528
RO.SIF3	Portfolio	-0.3723	0.0538	0.0514	-0.7333	0.0598	0.0475
	Benchmark	-0.3723	0.0538	0.0507	-0.9563	0.0782	0.0602
RO.SIF4	Portfolio	-0.3829	0.0709	0.0574	-0.7871	0.0574	0.0418
	Benchmark	-0.3829	0.0708	0.0568	-0.8662	0.0667	0.0488
RO.SIF5	Portfolio	-0.3636	0.0622	0.0529	-0.7564	0.0547	0.0384
	Benchmark	-0.3636	0.0622	0.0518	-0.9319	0.0756	0.0526

Details		In sample results			Out of sample results		
Symbol	Element	MDD*	SD**	SSD***	MDD*	SD**	SSD***
RO.SNP	Portfolio	-0.3123	0.0575	0.0350	-0.8069	0.0582	0.0438
	Benchmark	-0.4486	0.0631	0.0391	-0.8343	0.0717	0.0500
RO.TLV	Portfolio	-0.5122	0.0601	0.0344	-0.7959	0.0564	0.0353
	Benchmark	-0.4976	0.0617	0.0459	-0.9216	0.0674	0.0537
US.BAC	Portfolio	-0.2834	0.0326	0.0235	-0.5026	0.0399	0.0274
	Benchmark	-0.2837	0.0326	0.0234	-0.9344	0.0895	0.0580
US.GE	Portfolio	-0.1474	0.0285	0.0175	-0.6763	0.0362	0.0251
	Benchmark	-0.4633	0.0422	0.0275	-0.8270	0.0458	0.0334
US.IBM	Portfolio	-0.3308	0.0309	0.0195	-0.4880	0.0328	0.0223
	Benchmark	-0.4855	0.0428	0.0305	-0.4429	0.0298	0.0199
US.JNJ	Portfolio	-0.2426	0.0211	0.0155	-0.5700	0.0203	0.0158
	Benchmark	-0.3489	0.0251	0.0167	-0.3441	0.0202	0.0150
US.JPM	Portfolio	-0.3119	0.0407	0.0253	-0.6515	0.0473	0.0341
	Benchmark	-0.5990	0.0550	0.0391	-0.6814	0.0576	0.0357
US.KO	Portfolio	-0.2235	0.0288	0.0192	-0.2082	0.0218	0.0145
	Benchmark	-0.3491	0.0315	0.0233	-0.4061	0.0231	0.0163
US.PG	Portfolio	-0.2073	0.0226	0.0149	-0.5941	0.0206	0.0155
	Benchmark	-0.2074	0.0228	0.0144	-0.3901	0.0207	0.0147
US.T	Portfolio	-0.2058	0.0353	0.0208	-0.2567	0.0260	0.0175
	Benchmark	-0.4967	0.0481	0.0341	-0.4555	0.0280	0.0189
US.WMT	Portfolio	-0.2225	0.0284	0.0209	-0.7029	0.0266	0.0209
	Benchmark	-0.2818	0.0311	0.0217	-0.2620	0.0243	0.0167

Details		In sample results			Out of sample results		
Symbol	Element	MDD*	SD**	SSD***	MDD*	SD**	SSD***
US.XOM	Portfolio	-0.1735	0.0256	0.0161	-0.3686	0.0279	0.0196
	Benchmark	-0.3139	0.0327	0.0225	-0.3730	0.0290	0.0212
000270.KiaMtr	Portfolio	-0.4082	0.0581	0.0385	-0.9008	0.0638	0.0457
	Benchmark	-0.4464	0.0566	0.0381	-0.6433	0.0650	0.0441
003600.SK	Portfolio	-0.3920	0.0744	0.0398	-0.6146	0.0644	0.0414
	Benchmark	-0.3154	0.0748	0.0385	-0.7955	0.0693	0.0428
005380.HyundaiMtr	Portfolio	-0.2963	0.0411	0.0270	-0.6946	0.0495	0.0340
	Benchmark	-0.2973	0.0413	0.0270	-0.5859	0.0541	0.0362
005490.POSCO	Portfolio	-0.2762	0.0432	0.0302	-0.5660	0.0502	0.0327
	Benchmark	-0.2762	0.0431	0.0300	-0.6822	0.0529	0.0362
005930.Samsung	Portfolio	-0.2796	0.0414	0.0277	-0.7184	0.0422	0.0325
	Benchmark	-0.3621	0.0434	0.0306	-0.4662	0.0420	0.0290
012330.Mobis	Portfolio	-0.4872	0.0657	0.0412	-0.9841	0.0610	0.0500
	Benchmark	-0.5070	0.0665	0.0412	-0.5455	0.0528	0.0341
051910.LgChem	Portfolio	-0.4722	0.0544	0.0392	-0.9197	0.0731	0.0591
	Benchmark	-0.4725	0.0557	0.0400	-0.5725	0.0623	0.0362
053000.WooriFinance	Portfolio	-0.3059	0.0578	0.0382	-0.4833	0.0475	0.0315
	Benchmark	-0.3059	0.0578	0.0382	-0.8017	0.0648	0.0446
055550.ShinhanGroup	Portfolio	-0.2530	0.0506	0.0316	-0.8976	0.0493	0.0391
	Benchmark	-0.500	0.0598	0.0400	-0.6903	0.0506	0.0350
066570.LGElectronics	Portfolio	-0.5414	0.0607	0.0411	-0.9317	0.0599	0.0461
	Benchmark	-0.4005	0.0588	0.0371	-0.6655	0.0575	0.0413

*MDD = Maximum Drawdown
**SD = Standard Deviation
***SSD = Semi-Standard Deviation

Tabel 2. Risk measurements for best performing in sample trading rule

Region	Drawdown risk		
	In sample	Out of sample	Keeps or improves?
0	1	2	3
Romania	84.62%	92.31%	92.31%
United States	100.00%	60.00%	60.00%
South Korea	80.00%	30.00%	40.00%
TOTAL	87.88%	63.64%	66.67%

Region	Total risk		
	In sample	Out of sample	Keeps or improves?
0	4	5	6
Romania	46.15%	100.00%	100.00%
United States	90.00%	70.00%	70.00%
South Korea	60.00%	60.00%	70.00%
TOTAL	63.64%	78.79%	81.82%

Region	Downside risk		
	In sample	Out of sample	Keeps or improves?
0	7	8	9
Romania	38.46%	100.00%	100.00%
United States	80.00%	60.00%	70.00%
South Korea	30.00%	40.00%	70.00%
TOTAL	48.48%	69.70%	81.82%

Columns 1-2, 4-5, 7-8 report the percentage of times for which the investment risk of using the selected trading systems is lower than the one of the buy-and-hold strategy, grouped by risk category and trading period. Columns 3, 6 and 9 report the percentage of in sample best performing trading systems which kept or improved its risk characteristics versus the benchmark strategy in the confirmation period.

Appendix 3. Data snooping bias example for SIF1

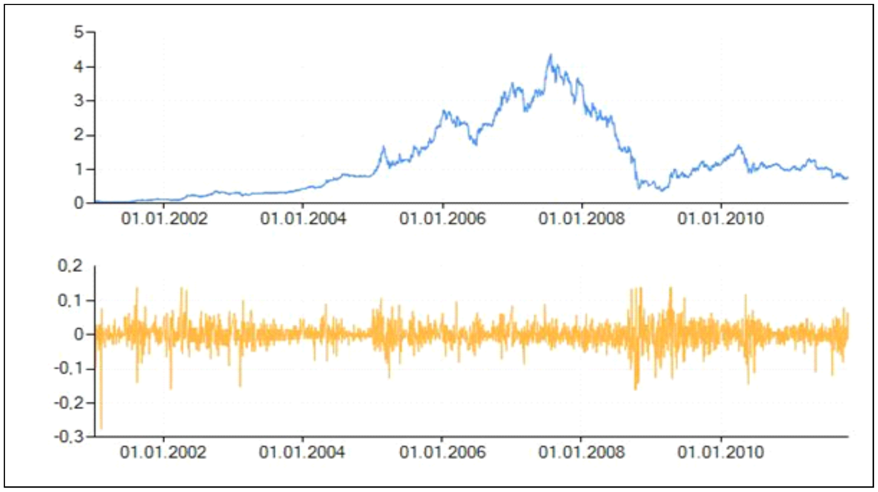

Figure 1: Closing price and daily return of SIF1 starting January 2001 to October 2011 (unadjusted values).

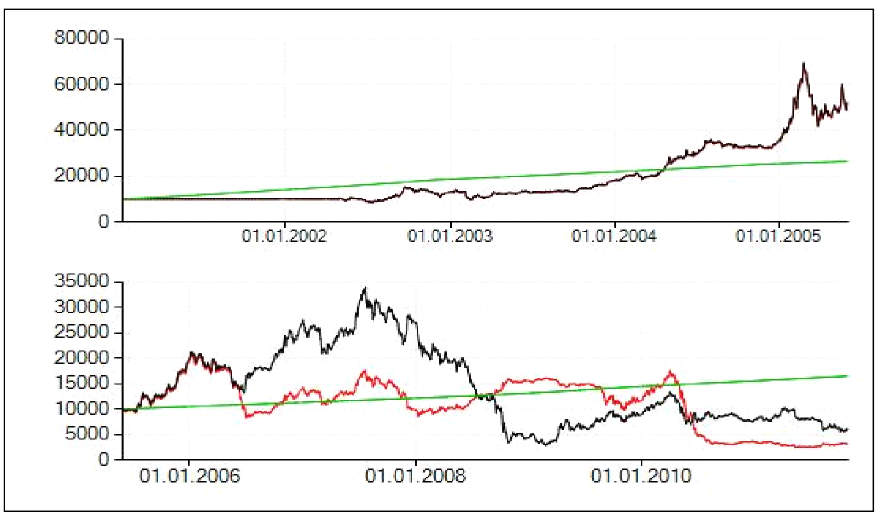

Figure 2: Evolution of investment portfolio, benchmark portfolio and risk free portfolio for both in-sample period (top chart; January 2001 – February 2005) and out-of-sample period (bottom chart; March 2005 – October 2011).

Appendix 4. Calculating geometric M2 for Sortino excess return (ExM2S)

a. Sortino ratio:

$$SR = \frac{r_p - r_b}{\sigma^d} \tag{8.1}$$

where:
- r_p = investment portfolio total return;
- r_b = benchmark portfolio total return;
- σ^d = downside risk of portfolio return;

b. Sortino M2 return:

$$M2^S = r_p + SR\left(\sigma_b^d - \sigma^d\right) \tag{8.2}$$

where:
- σ_b^d = downside risk of benchmark portfolio;

From (8.1) and (8.2), the following derived formula can be written for $M2^S$:

$$M2^S = r_b + (r_p - r_b)\,\frac{\sigma_b^d}{\sigma^d} \tag{8.3}$$

c. Geometric M2 for Sortino excess return:

$$ExM2^S = \frac{1 + M2^S}{1 + r_b} - 1 \tag{8.4}$$