International Journal of Business, Human and Social Sciences
ISSN: 2517-9411
Vol:5, No:11, 2011

Technical Trading Rules in Emerging Stock Markets

Stefaan Pauwels, Koen Inghelbrecht, Dries Heyman, and Pieter Marius

Abstract**—**Literature reveals that many investors rely on technical trading rules when making investment decisions. If stock markets are efficient, one cannot achieve superior results by using these trading rules. However, if market inefficiencies are present, profitable opportunities may arise. The aim of this study is to investigate the effectiveness of technical trading rules in 34 emerging stock markets. The performance of the rules is evaluated by utilizing White's Reality Check and the Superior Predictive Ability test of Hansen, along with an adjustment for transaction costs. These tests are able to evaluate whether the best model performs better than a buy-and-hold benchmark. Further, they provide an answer to data snooping problems, which is essential to obtain unbiased outcomes. Based on our results we conclude that technical trading rules are not able to outperform a naïve buy-and-hold benchmark on a consistent basis. However, we do find significant trading rule profits in 4 of the 34 investigated markets. We also present evidence that technical analysis is more profitable in crisis situations. Nevertheless, this result is relatively weak.

Keywords**—**technical trading rules, Reality Check, Superior Predictive Ability, emerging stock markets, data snooping

I. INTRODUCTION

ONE of the most discussed topics in financial literature is the efficiency of speculative markets. If financial markets are fully efficient, future prices can't be predicted based on past price movements, which eliminates the usefulness of technical trading rules. However Lo [1] introduces the Adaptive Market Hypothesis, in which the relationship between risk and return is claimed not to be stable over time. Hence, the efficiency of markets is considered to be a dynamic process. This means that profitable technical trading opportunities may occur from time to time. In addition, recent literature (e.g., McKenzie [2], Marshall, Cahan and Cahan [3]) shows that inefficiencies may occur in emerging stock markets, which is in favor of technical analysis. We use these insights to investigate whether 34 worldwide emerging stock markets provide a basis for technical trading rules.

In this research, we contribute to the literature in several ways. Firstly, a total of 11,350 technical trading algorithms are drawn from 13 strategies, which is one of the largest number of models ever used in a survey of this kind. Furthermore, this sample is tested on 34 emerging stock market indices, while previous research tends to focus on one or a few markets. Thirdly, we compare the results of the best trading rule to the full universe of rules. We use a new test for superior predictive ability (SPA). The new test improves favorably to the reality check for data snooping (RC), because it is more powerful and less sensitive to poor and irrelevant rules. The Superior Predictive Ability test is a test that can be used for comparing the performances of several technical trading rules. The forecasts are evaluated using a loss function, and the best rule is the one that produces the smallest expected loss. This approach is introduced by White [4] and supported by Sullivan, Timmermann and White [5], Hansen [6], and Hsu, Hsu and Kuan [7]. According to their work, one is able to eliminate data snooping problems by using this method, which is essential to achieve unbiased results. Finally, this survey provides an adjustment for transaction costs. As far as we know, a research of this extent hasn't been executed yet on emerging stock markets.

We find that technical analysis is significantly profitable in only 4 of the 34 countries after accounting for data snooping bias and transaction costs. Strong evidence is found for the fact that data snooping has an immense effect on technical trading rule performance evaluation. Further, evidence is presented that trading algorithms performed better during the recent economic crisis, which proves that market inefficiencies emerge from time to time. It is important to notice that this study only examines historical outperformance of technical trading rules. It still remains an open question how to detect the best trading rule ex ante.

The remainder of this paper is structured as follows: Section II gives a review on the existing literature related to our survey, section III describes the data, section IV sets out the methodology, section V discusses the results, and section VI concludes.

II. LITERATURE REVIEW

Technical trading rules are one of the oldest and most used techniques to forecast price movements in various financial markets. These methods are applied by economists to analyze the evolution of stock prices, and to detect buy and sell signals. For that reason, this subject has been widely studied by academics. Nevertheless, literature indicates that researchers are not able to present an unambiguous conclusion on technical analysis.

According to the efficient market hypothesis of Fama [8], security prices fully reflect all publicly available information. This implies that stock prices change randomly, and that it is impossible to forecast future security prices when studying information gained from past prices. Consequently, technical analysis does not add value. Proponents of this theory are Jensen [9], Malkiel [10]-[11], Li and Wang [12] and Chen,

Stefaan Pauwels. Department of Financial Economics, Ghent Univeristy, Ghent University, Woodrow Wilsonplein 5D (phone: +32498676446; e-mail: stefaan.pauwels@ugent.be).
Koen Inghelbrecht, Department of Financial Economics, Ghent Univeristy, Ghent University, Woodrow Wilsonplein 5D (e-mail: koen.inghelbrecht@ugent.be).
Dries Heyman, Department of Financial Economics, Ghent Univeristy, Ghent University, Woodrow Wilsonplein 5D (e-mail: dries.heyman@ugent.be).
Pieter Marius, Financial Data Management, Dexia (e-mail: npieter.marius@dexia.com)

Huang and Lai [13]. On the other hand, academics as Lukac, Brorsen, Irwin [14], Brock, Lakonishok, and LeBaron [15], Sullivan, Timmermann and White [5], Gunasekarage and Power [16], Fifield, Power and Sinclair [17], Marshall, Cahan and Cahan [3] and Hsu, Hsu and Kuan [7] find positive evidence regarding the profitability of technical trading rules. We must emphasize that there still is no conclusive evidence on this subject. The field of technical trading rules is too complex and too evolving to draw definitive conclusions.

A. Evidence from developed stock markets

Over the years, numerous financial economists have found predictable patterns in stock prices, which mean that technical analysis may generate excess returns.

Important evidence in support of technical analysis in stock markets is provided by Brock, Lakonishok and LeBaron [15] (BLL, hereafter). In their survey they do not take transaction costs into account. Further, they are aware that data snooping may occur, superior trading rule performance is often a consequence of survivorship bias. When examining popular trading rules, BLL acknowledge that their superior results may be the consequence of luck. Bessembinder and Chen [18] argue that technical trading requires regular transactions. Therefore, they extend the survey of BLL by making a correction for transaction costs. While doing that, Bessembinder and Chen [18] find that the positive evidence of BLL disappears. Still, data snooping bias is not taken into account.

As an answer on these surveys, White [4] introduces the bootstrap Reality Check. He states that to mitigate data snooping problems, survivorship bias has to be countered. The only way to handle this problem is to compose a full universe of trading rules, instead of only investigating successful rules. The Reality Check tests the performance of the best technical trading rule in the context of the full universe of rules. By employing a performance statistic to the full set of models, this statistical procedure counters data snooping bias. Sullivan, Timmermann, and White [5] (STW, hereafter) utilize the Reality Check to evaluate technical trading profitability in the U.S. stock market, and find supportive evidence for the results of BLL in the period 1897-1986. Nevertheless, they find no proof of excess returns in the period 1987–1996, which was not in the sample of BLL. This evolution in empirical results may have various causes. First of all, the structure of stock markets may have changed over the years. Secondly, there is a possibility is that technical trading rules lose their predictive power when they are made public. This effect is investigated by Timmermann and Granger [19]. They notice that when the trading algorithms are published, the information they deliver is incorporated in stock prices. Therefore it will be impossible to consistently use the rules to beat the market. Thus, Timmermann and Granger conclude that the early users of technical trading rules may be able to achieve profitable results, but after publication, superior performance will not persist. Technical analysis is, in other words, self-destructive. This viewpoint is in support of Lo's Adaptive Market Hypothesis, which stated that market efficiency has to be seen as an evolutionary process. Although White presents a model that is able to make a correction for data snooping, Hansen [6] discovers some shortfalls. He states that the p-values the RC test delivers are inconsistent. Hansen claims that the Reality Check is sensitive to the inclusion of poor and irrelevant models, and consequently can be manipulated. Therefore, he introduces a new test for Superior Predictive Ability, which corrects the errors made by White. Hansen improves the Reality Check by using a studentized test statistic and a data-dependent null distribution. Because of these changes, this procedure will be less sensitive when poor performing trading are included in the sample. Empirical work of Hansen and Lunde [20], Hsu, Hsu and Kuan [7] shows that Hansen's test for Superior Predictive Ability is more powerful than White's Reality Check.

In recent work of Marshall, Qian and Young [21], the conclusion is made that technical traders are not able to consistently beat the benchmark in the U.S. stock market from 1990 until 2004. However, evidence is presented that technical analysis is more applicable on small and illiquid stocks, which are likely to be present in emerging stock markets.

B. Evidence from emerging stock markets

The overall conclusion is that in most cases technical analysis is not profitable in financial markets of highly developed countries, which supports at least the weak form of the efficient market hypothesis. Further, literature provides evidence that the predictive power of technical trading algorithms has decreased over the years. Nevertheless, researches raise questions about the efficiency of emerging markets. Lo and McKinlay [22], Fama and French [23], and McKenzie [2] indicate that inefficiencies may be present in these markets, which provides opportunities for technical analysis. As mentioned before, Marshall, Qian and Young [21] conclude that technical trading rules are more applicable on small, illiquid stocks. Furthermore, proponents of the Adaptive Market Hypothesis also indicate that younger stock markets provide more arbitrage opportunities compared to developed markets. In recent literature, a lot of economists use these insights to test technical trading benefits in emerging stock markets.

Gunasekarage and Power [16] uncover evidence that technical analysis indeed provides arbitrage opportunities in emerging markets. They investigate moving average rules in the stock markets of Bangladesh, India, Pakistan and Sri Lanka. Gunasekarage and Power find that in all of the countries except for India, the rules significantly outperform a naïve buy-and-hold portfolio. These results support the findings of Lo and McKinlay [22], Fama and French [23], and McKenzie [2], since India is the largest and most efficient market included in the sample of this survey.

Fifield, Power and Sinclair [17] then, examine whether or not two widely used technical trading rules – filter rules and moving averages - have been profitable in 11 European stock markets in the period 1991-2000. They find evidence of filter rule profits in 4 emerging markets - Greece, Hungary, Turkey and Portugal -, but when results of developed markets are considered, there is no evidence of superior performance. These results seem to indicate that the diversity in development of stock markets is more determinative for technical analysis profitability than geographical location.

A survey of Li and Wang [12] investigates technical analysis on the Chinese stock market, which is the largest emerging market in terms of market capitalization. they make a distinction between A-shares, which are reserved for domestic investors and B-shares, which are reserved for foreign investors. After transaction costs are included, they find no evidence of superior technical trading rules when considering A-shares. However, Li and Wang find excess returns when investigating B-shares. Since February 19, 2001, domestic investors are also permitted to trade B-shares. Li and Wang conclude that after this change in legislation, excess technical trading profits disappear.

Support for the efficient market hypothesis is provided by Chen, Huang and Lai [13], who find that positive technical trading results in eight Asian equity markets disappear when transaction costs and data snooping are taken into account. Another survey that investigates moving average rules in emerging stock markets is provided by Papathanasiou and Samitas [24]. They use the methodology of Brock, Lakonishok and LeBaron [15] and apply it on the Cyprus Stock Exchange, which is a small and non derivative market. Papathanasiou and Samitas state that when transaction costs are ignored, the trading rules significantly outperform a buy-and-hold strategy over the 1998–2005 period. McKenzie [2] investigates technical trading profitability in 17 emerging stock markets relative to a U.S. benchmark. He states that some of the trading algorithms are able to achieve excess returns, and that the persistence of these results is more likely to appear in emerging markets.

We have to note that the above-mentioned studies on emerging markets do not acknowledge data snooping bias. Hsu, Hsu and Kuan [7] take this problem into account. They investigate technical trading profitability in Asian emerging stock markets (MSCI Emerging Markets Index, MSCI Brazil Index, MSCI South Korea Index, MSCI Malaysia Index, MSCI Mexico Index, and MSCI Taiwan Index), and use a stepwise test for Superior Predictive Ability. Hsu, Hsu and Kuan find that technical trading rules perform better in young stock markets than in developed markets. More, they provide further evidence in favour of Lo's [1] Adaptive Market Hypothesis, by stating that the profitability of technical analysis weakens over the years.

Other research that provides an answer on data snooping bias is conducted by Marshall, Chan and Chan [3]. They give a straightforward view on how White's Reality Check can be used to examine technical trading rule profitability. They test more than 5,000 trading rules on the 23 developed markets and the 26 emerging markets of the Morgan Stanley Capital Index, and report that the best performance is achieved in emerging stock markets. Nevertheless, Marshall, Chan and Chan conclude that the significance of the results is not strong enough exclude the possibility that the results are obtained due to luck.

III. Data

A. Stock market indices

Unlike many previous studies that focus on one or a few markets, we test profitability of technical trading rules on a larger sample of indices. We apply each model on the end-of-day returns of 34 worldwide emerging stock markets. The reason why we focus on these specific countries is because of the fact that recent literature of Fifield, Power and Sinclair [17] and Marshall, Chan and Chan [3] has shown that superior outcomes are more likely to appear in emerging stock markets. We test whether these positive results will emerge when transaction costs and data snooping bias are taken into account. For each stock index, we use the longest possible time window. Further, we also examine a sub-period that represents the recent economic crisis, since market inefficiencies are likely to be present in this period. The summary statistics are presented in table I.

B. Technical trading rules

In order to achieve satisfactory results, it is very important to select a well composed sample of technical trading rules. In this paper, we have selected 13 trading systems, based on previous research of Lukac, Brorsen, Irwin [14], Sullivan, Timmermann and White [5], Hsu and Kuan [25] and Park and Irwin [26]. Each trading rule can be assigned to different categories: moving averages filter rules, channel breakouts, and momentum oscillator rules. A total 11,350 technical trading rules are drawn from these trading strategies.

1) Moving Averages

The most popular technical trading systems are moving averages. These models can be obtained by calculating the average of a fixed sample size of stock prices. For each day, a new average will be calculated. The plot line that is constructed by taking all the averages into account is called a moving average. The goal of moving average systems is to rule out the possibility that false trading systems will be generated by short-term price changes. Instead, long-term price trends can be detected. In this survey we use 5 moving average systems: Simple Moving Average with a band (MAB), Dual Moving Average Crossover (DMC), Moving Average Crossover (MAC), Exponential Moving Average Crossover (EMC) and Moving Average Convergence-Divergence (MACD).

2) Filter Rules

Like moving averages, filter rules try to avoid false trading systems that are based on short-term price changes. Therefore these strategies filter out small price movements, and only generate trading signals in the case of larger price changes. In this paper, the Alexander's Filter Rule (ALX) is used.

3) Price Channels

The third category of technical trading systems that we use in our survey is the price channel. Sometimes this strategy is called support and resistance or trading range breakout. Trading signals are generated when a current price level passes the highest high or lowest low in a predefined time interval. We utilize 2 price channel systems: Outside Price Channel (CHL) and Bollinger Bands (BBA).

4) Momentum Oscillator Rules

Momentum rules utilize the magnitude of price changes to detect trading signals. They generate long (short) signals when a momentum indicator is greater (less) than a predefined threshold value. In this survey, the 5 following momentum oscillator rules are used: Relative Strength Index (RSI), Directional Indicator (DRI), Reference Deviation (REF), Williams %R (WR) and Stochastic Oscillator (STO).

C. Transaction costs

To obtain reliable results, we impose transaction costs on each trade. The figures are based on literature of Munck [27] and Elkins/McSherry consultancy (2008). Unlike many previous studies that base their estimations process on dated research, our survey gives a realistic view on the actual situation.

IV. Methodology

In order to examine the profitability of technical trading rules relative to a given benchmark, we need a statistical procedure that provides a test across the entire set of algorithms. Such a model is presented by White [4]. Building on previous research of Diebold and Mariano [28] and West [29], he introduces a Bootstrap Reality Check (RC). By testing the null hypothesis that the benchmark outperforms the entire set of technical trading rules, Sullivan, Timmermann and White [5] provide evidence that the RC-test is able to rule out data snooping bias.

Firstly, the Reality Check derives the performance of the trading rules relative to the benchmark by interpreting the mean return. If the predicted return of a trading rule t is $\hat{Y}_t$, and the realized return is Y_t, we can define its loss as $L(Y_t, \hat{Y}_t)$. The best rule will be the one with the smallest loss. The relative performance of trading rule k at time t, compared to the benchmark model, can be formulated as following:

$$f_k(t) \equiv L(Y_t, \hat{Y}_{o,t}) - L(Y_t, \hat{Y}_{k,t}), \quad k = 1,\ldots, m, \quad t = 1,\ldots, n.$$

In order to find out whether the models k = 1,…, m are able to produce excess returns, we test the hypothesis that the benchmark is not inferior to any of the trading rules. Let u_k be the expected return of model k towards the benchmark. The hypothesis can be presented as following:

$$u_k = E[f_k(t)] \leq 0, \ \ k = 1,\ldots, m.$$

In case that for each technical trading rule k (k = 1,..., m), $u_k \equiv E(f_k)$ is well-defined, we can formulate an m-dimensional vector u by

$$u = \begin{pmatrix} u_1(t) \\ u_m(t) \end{pmatrix} \ E = \begin{pmatrix} f_1(t) \\ f_m(t) \end{pmatrix},$$

The hypothesis that the benchmark model is the best performing model can be defined in several ways. Derived from the previous equations we can state that we want to test the hypothesis H_0: $u_k \leq 0$ for k = 1,…, m. An equivalent formulation for the vector is the following:

$$H_0 = u \leq 0.$$

Next, the stationary bootstrap method of Politis and Romano [30] is used to generate pseudo time series from f_k. The number of bootstrap replications is set at 500, as in Sullivan, Timmermann and White [5] and Hsu, Hsu and Kuan [7]. Brock, Lakonishok and LeBaron [14] state that p-values are not sensitive for a bootstrap replication size larger than 500. To acknowledge the length of our dataset, the block length is set at $t^{\wedge (1/3).}$ This approach is supported by Politis and White [31].

White [4] continues by constructing the following test statistic from the original technical trading returns and the 500 bootstrapped time series.

$$T_n^{RC} = \max_{1<k<m} n^{1/2}\bar{f}_k \qquad T_n^{RC,B} = \max_{1<k<m} n^{1/2}(\bar{f}_k^B - \bar{f}_k),$$

The variable $\bar{f}_k$ is calculated as following:

$$\bar{f}_k = \frac{1}{n}\sum_{t=1}^{n} \bar{f}_k(t),$$

By comparing T_n^{RC} and $T_n^{RC,B}$, we derive White's Reality Check p-value for the null hypothesis. However, Hansen [20] finds that this p-value can be manipulated when poor and irrelevant models are included. Therefore, he introduces the Superior Predictive Ability test (SPA), which changes the procedure of the Reality Check on two levels. Firstly, Hansen uses a studentized test statistic, in order to avoid the comparison of models which have different units of standard deviation. Secondly, Hansen utilizes a sample dependent null distribution. When executing the RC-test, all the trading rules are used to test the H_0-hypothesis, which means that poor performing and irrelevant trading rules may influence the data snooping adjusted p-value. As an answer on this, Hansen's lower and consistent SPA p-values are introduced. Firstly, one has to determine which models perform worse than the benchmark. The lower bound p-value excludes all models that have higher losses than that benchmark. The consistent p-value is the true p-value of the SPA test. This procedure excludes all models that perform worse than the threshold value $-2\sqrt{\log\log n}$. This truncation point assures that irrelevant models are excluded from the SPA test. The test statistic is constructed as following:

$$T_n^{SPA} \equiv \max_{k=1,\dots,m} \frac{n^{1/2}\bar{f}_k}{\hat{\sigma}_k} \qquad T_n^{SPA,B} \equiv \max_{k=1,\dots,m} \frac{n^{1/2}(\bar{f}_k^B - \hat{u}_k^c)}{\hat{\sigma}_k},$$

With $\hat{\sigma}_k^2 = \widehat{\mathrm{var}}(n^{1/2}\bar{f}_k)$ as an estimator for variance in return, and $\hat{u}_k^c = \bar{f}_k 1_{n^{1/2}\bar{f}_k/\hat{\sigma}_k \le -2\sqrt{\log\log n}}$ as the threshold value that is used to remove the poor and irrelevant models. By comparing T_n^{SPA} and $T_n^{SPA,B}$, we derive the consistent SPA p-value for the null hypothesis.

In this survey, we will use three data snooping adjusted p-values. The upper bound of our test is the conservative Reality Check p-value. The lower bound is the SPA lower p-value, while for the true p-value, we use the SPA consistent p-value.

V. Results

In Table II and III we discuss the performance statistics of the trading models, before and after transaction costs. By interpreting the nominal p-values, before transaction costs, we can state that before accounting for data snooping, the performance of technical trading rules is strongly significant in all stock markets, except for Brazil and Latvia. These results are not surprising, as they correspond with literature on technical analysis in emerging markets, such as surveys of Gunasekarage and Power [16] and Chen, Huang and Lai [13]. After an adjustment of transaction costs is made, we still conclude that technical analysis is useful in the majority of the investigated stock markets. This positive evidence disappears when testing the performance of the best rule relative to the entire set of models. When looking at the difference between the consistent SPA p-value and nominal p-value, we find that data snooping has a huge influence on the performance of the best trading rule. For example in the case of Venezuela (table III), we find a significant nominal p-value of 0.000. Nonetheless, the consistent p-value that is produced by the Superior Predictive Ability Test equals 0.8180. After correcting for data snooping and transaction costs, significant excess returns are only found in the stock markets of Botswana, Jamaica, Kenya and Oman. The results are especially strong for Kenya, which yields a consistent SPA p-value of 0.000.

When interpreting Table II and III, we also can state that in the absence of transaction costs, the Alexander Filter rule with a filter size of 0.5%, the 2 day Bollinger Band, and the 3 day Relative Strength Index are the best performing models in the majority of investigated markets. These specific rules often appear among the 10 best performing trading rules in the other stock market indices. After considering transaction costs, these results do not persist. An explanation for these outcomes can be found in the number of trading signals the algorithms produce. Because of the fact that the aforementioned models trade on small filter sizes and short time windows, trading signals emerge frequently. This implies that holding periods are very short, and transaction costs high. Consequently, the best returns when accounting for these trading costs appear for trading systems which trade less frequently. Examples are long-run oriented Exponential Moving Average Crossover Rules and Alexander Filter Rules with large filter sizes. As presented in Table IV, the holding periods for these trading rules are longer. The results correspond with research of Chen, Huang and Lai [13].

The best rules for each country that are presented in Table IV and V reveal very interesting information. Firstly, we find that in the majority of markets, technical trading rules generate more losing trades than winning trades. One would think that this is in support of the Efficient Market Hypothesis. Nevertheless, these models are still able to produce positive returns over the entire sample period. This is due to the fact that the profits that are achieved by the winning trades exceed the losses that are generated by the losing trades. The market in the period of research was very bullish, which might explain these exceeding long profits.

This study also uncovers remarkable differences in profitability between short trades and long trades. In the full sample period, long trades tend to be more successful than short trades, which support earlier research of Sullivan, Timmermann and White [5]. This result is observed on the level of average return per trade. In a reasonable number of markets, the differences are huge. For example for Mexico, we find that the average return per long trade is equal to 3,47%, while the average return per short trade is only 0.20%. This result is caused by the fact that the hit rate of long trades is significantly higher than the hit rate of short trades. Further long trades seem to have a longer holding period than short trades. These outcomes are very strong, since they occur all of investigated markets except for Hungary, Ecuador and Lebanon. In table VIII and IX, the same statistics per best trading rule are presented for the crisis period. The results contrast sharply with the statistics from the entire sample. During the crisis, short trades tend to be much more successful than long trades on the level of average return per trade. Further, the holding period of short positions is longer than for long positions. This result is not surprising, since the majority of markets are in a downward trend during the crisis.

In table VII and VI, we present the same statistics for the subsample of the recent economic crisis. We find that very different types of trading systems are identified as being the best performing model. Further, there is very little connection between the best performer during the full sample period, and the best rule during the crisis subsample. This means that the performance of the algorithms seems to be very data-dependent. Remarkably, we find that during the crisis the Moving Average Convergence Divergence system is among the best performing algorithms, while this particular model underperforms most trading rules during the full sample period.

Table VI provides an overview of the same performance statistics for the subsample. We find during the crisis period significant data snooping adjusted p-values in Nigeria, Kenya, Zambia, Botswana, Lithuania, Bulgaria and Estonia. These results are obtained after a consideration of data snooping and transaction costs. It is interesting to notice that these excess returns are found either in African or in East European markets. Further, we find that for 22 markets the mean daily return is higher during the sub period compared to entire sample period. The abovementioned results may mean that market inefficiencies are more likely to appear during crisis periods. Nevertheless, we conclude that even during these periods, it is very difficult to make profits on a consistently basis by using technical analysis.

Important to notice is that in some markets – Latvia and Ecuador -, data snooping adjusted p-values after accounting for transaction costs are more significant than the p-values before making this adjustment. The reason for these outcomes is due to the fact that in both situations, the same trading rule is detected as best performer. This specific algorithm produces very few trading signals, which implies that transaction costs remain low. Consequently, the other models will suffer more from the adjustment for transaction costs than the best rule, and the performance of this algorithm relative to the entire set of rules will be more significant.

As expected, our results indicate differences between the RC-test and SPA-test. These outcomes are in support of research of Hansen [6] and Hansen and Lunde [20], who state that the inclusion of one or more poor performing models can have a large influence on the Reality Check p-value. This can have a large impact on the conclusions of a survey. Consider the performance statistics of Botswana. When interpreting the RC p-value, which is equal to 0.0560, one would conclude that the best trading rule is not able to outperform the buy-and-hold benchmark. However, when we inspect the consistent SPA p-value, which signals 0.0360, one would state that the H_0-hypothesis that the benchmark is the best model should be rejected. These results indicate that the Reality Check unfairly punishes the best performing trading rule when a large number of poor performing models are present.

VI. Conclusion

Over the years, there has been a large academic interest in the usefulness of technical trading rules. A fundamental problem is to take the whole universe of trading algorithms into consideration when testing their performance. Our survey addresses this issue by composing a very large number of trading rules, and by using White's [4] Reality Check and Hansen's [6] Test for Superior Predictive Ability. By using these methods, we are able to provide strong evidence that data snooping bias has an immense effect on technical trading rule performance evaluation. We conclude that when adjustments for transaction costs and data snooping bias are made, technical trading rules are not able to outperform a passive buy-and-hold strategy on a consistently basis, except for 4 countries. Further, we provide evidence that during the recent economic crisis, market inefficiencies were present in 7 investigated markets. We also indicate that the algorithms make more losing trades than winning trades. Further, we find significant differences between short trades and long trades. When considering the full sample period, the results are in favor of long trades, while during the crisis, results reveal the opposite. This may mean that the investigated trading rules still have room for improvement and refinement.

Important to notice is that this only examines historical performance of technical analysis. We do not present evidence that investors are capable of detecting the best technical trading rule ex ante. Further, it can be interesting to extend this study by testing the profitability of combination systems, which generate trading signals when two or more trading systems are in accordance with each other. Notice, however, that even if these trading rules achieve higher returns, this will not automatically lead to more significant results. The effect of testing technical trading profitability in a larger set of trading rules may dominate the improved performance of the best trading rule, leading to higher data snooping adjusted p-values.

References

[1] Lo, A. (2004). The adaptive markets hypothesis: Market efficiency from an evolutionary perspective, Journal of Portfolio Management, 30, 15–29.
[2] McKenzie, M.D. (2007). Technical Trading Rules in Emerging Markets and the 1997 Asian Currency Crises, Emerging Markets Finance and Trade, 43, 46-73.
[3] Marshall, B., Cahan, R.C., Cahan, J.M. (2010) Technical Analysis Around The World, working paper, Massey University New Zealand.
[4] White, H. (2000). A Reality Check for data snooping, Econometrica, 68, 1097-1126.
[5] Sullivan, R., Timmermann, A., White, H. (1999). Data snooping, technical trading rule performance, and the bootstrap, Journal of Finance 54, 1647-1691.
[6] Hansen, P.R. (2005). A test for Superior Predictive Ability, Journal of Business & Economic Statistics, 23, 365-380.
[7] Hsu, P.H., Hsu Y.-C., Kuan, C.H. (2010). Testing the Predictive Ability of Technical Analysis Using a New Stepwise Test without Data Snooping Bias. Journal of Empirical Finance, 17:3, 471-484.
[8] Fama, E. (1970). Efficient capital markets: a review of theory and empirical work, Journal of Finance, 25, 25-52.
[9] Jensen, M.C. (1968). The performance of mutual funds in the period 1945–1964, Journal of Finance, 23, 389–416.
[10] Malkiel, B.G. (1973). A Random Walk Down Wall Street, New York, Norton, 1-428.
[11] Malkiel, B.G. (2003). The efficient market hypothesis and its critics. Journal of Economic Perspectives, 17, 59–82.
[12] Li, W., Wang, S.W. (2007). Ownership Restriction, Information Diffusion Speed, and the Performance of Technical Trading Rules in Chinese Domestic and Foreign Shares Markets, Review of Pacific Basin Financial Markets and Policies, 10:4, 585-617.
[13] Chen, C-W., Huang, C-S., Lai, H-W. (2009). The impact of data snooping on the testing of technical analysis: An empirical study of Asian stock markets. Journal of Asian Economics, 20, 580-591.
[14] Lukac, L.P., Brorsen, B.W., Irwin, S.H. (1998). A Test of Futures Market Disequilibrium using Twelve Different Technical Trading Systems, Applied Economics, 20, 623-639.
[15] Brock, W., Lakonishok, J., LeBaron, B. (1992). Simple technical trading rules and the stochastic properties of stock returns, Journal of Finance, 47, 1731-1764.
[16] Gunasekarage, A., Power, D.M. (2001). The Profitability of Moving Average Trading Rules in South Asian Stock Markets, Emerging Markets Review, 2, 17-33.
[17] Fifield, S., Power, D., Sinclair, D. (2005). An analysis of trading strategies in eleven European stock markets, European Journal of Finance, 11, 531-548.
[18] Bessembinder, H., Chan, K. (1998). Market Efficiency and the Returns to Technical Analysis. Financial Management, 27, 5-17.
[19] Timmermann, A., Granger, C.W.J. (2004). Efficient market hypothesis and forecasting, International Journal of Forecasting, 20, 15–27

[20] Hansen, P.R., Lunde A. (2005). A forecast comparison of volatility models: Does anything beat a GARCH(1,1)? Journal of Applied Econometrics, 20, 873–889.
[21] Marshall, B., Qian, S., Young, M. (2009). Is technical analysis profitable on US stocks with certain size, liquidity or industry characteristics?, Applied Financial Economics, 19, 1213-1221.
[22] Lo, A., McKinlay, C. (1988). Stock Do Not Follow Random Walks, Review of Financial Studies (Spring), 41-66.
[23] Fama, E., French, K. (1988). Permanent and Temporary Components of Stock Prices, Journal of Political Economy, 96:2, 246-274.
[24] Papathanasiou, S., Samitas A. (2010). Profits from Technical Trading Rules: The Case of Cyprus Stock Exchange, Journal of Money, Investment and Banking, 13, 35-43.
[25] Hsu, P.H., Kuan, C.H. (2005). Re-examining the profitability of technical analysis with data snooping checks. Journal of Financial Econometrics, 3, 606–628.
[26] Park, C.H., Irwin, S.H. (2010). A Reality Check on Technical Trading Rule Profits in the U.S. Futures Market. Journal of Futures Markets,30:7, 633-659.
[27] Munck, N.H. (2005). When Transactions Went High-Tech: A Cross-Sectional Study of Equity Trading Costs in the Light of More Sophisticated Trading Systems, SSRN Working Paper.
[28] Diebold, F.X., Mariano, R.S. (1995). Comparing Predictive Accuracy, Journal of Business and Economic Statistics, 13, 253-263.
[29] West, K.D. (1996). Asymptotic Inference About Predictive Ability, Econometrica, 64, 1067-1084.
[30] Politis, D.N., Romano, J.P. (1994). The Stationary Bootstrap. Journal of the American Statistical Association, 89, 1303-1313.
[31] Politis, D.N., White, H. (2004). Automatic Block-Length Selection for the Dependent Bootstrap, Econometric Reviews, 23:1, 53-70.

TABLE I
SUMMARY STATISTICS
THIS TABLE REPORTS THE SUMMARY STATISTICS FOR 34 EMERGING STOCK MARKET INDICES. FOR EACH COUNTRY, THE LONGEST POSSIBLE SAMPLE PERIOD IS USED. TRANSACTION COSTS ALTER FOR EACH SPECIFIC INDEX

Country	Sample Period		Number of observations	Transaction costs	Average return per year
	start	end			
Argentina	20 December 1993	28 February 2011	4486	0,42%	16,49%
Bahrain	22 May 2003	28 February 2011	2028	0,35%	4,29%
Botswana	17 September 2001	28 February 2011	2466	0,35%	12,00%
Brazil	10 May 1990	28 February 2011	5428	0,40%	94,85%
Bulgaria	9 March 2001	28 February 2011	2602	0,35%	20,00%
Chile	22 May 1987	28 February 2011	6202	0,35%	18,58%
Colombia	20 November 2001	28 February 2011	2420	0,55%	31,61%
Czech Republic	24 August 1994	28 February 2011	4309	0,37%	5,63%
Ecuador	20 December 1993	28 February 2011	4486	0,35%	-1,40%
Egypt	22 May 1995	28 February 2011	4116	0,56%	14,02%
Estonia	22 May 2000	28 February 2011	2811	0,40%	16,16%
Hungary	22 May 1991	28 February 2011	5159	0,37%	18,13%
India	22 May 1987	28 February 2011	6202	0,59%	18,34%
Indonesia	22 August 1983	28 February 2011	7182	0,52%	15,63%
Jamaica	29 October 1987	28 February 2011	6088	0,35%	17,75%
Jordan	10 April 1989	28 February 2011	5711	0,35%	9,37%
Kenya	31 May 1990	28 February 2011	5413	0,35%	9,38%
Kuwait	17 May 1995	28 February 2011	4119	0,35%	31,92%
Latvia	22 May 2000	28 February 2011	2811	0,40%	14,78%
Lebanon	10 Juin 1996	28 February 2011	3841	0,35%	5,28%
Lithuania	22 May 2000	28 February 2011	2811	0,40%	14,24%
Malaysia	21 May 1980	28 February 2011	8029	0,41%	8,01%
Mexico	23 May 1988	28 February 2011	5941	0,40%	25,56%
Morocco	22 May 2002	28 February 2011	2289	0,35%	15,35%
Nigeria	2 Juin 2000	28 February 2011	2802	0,35%	15,56%
Oman	11 March 1997	28 February 2011	3645	0,35%	7,95%
Pakistan	19 May 1989	28 February 2011	5682	0,35%	15,66%
Poland	19 January 1996	28 February 2011	3146	0,42%	11,36%
Romania	6 February 1998	28 February 2011	3407	0,35%	19,65%
Russia	8 February 1999	28 February 2011	3941	0,32%	29,94%
South Africa	17 November 1995	28 February 2011	3987	0,38%	13,26%
Turkey	23 May 1988	28 February 2011	5941	0,38%	48,40%
Venezuela	19 August 1993	28 February 2011	4573	0,83%	27,28%
Zambia	22 May 1997	28 February 2011	3593	0,35%	25,59%

International Journal of Business, Human and Social Sciences
ISSN: 2517-9411
Vol:5, No:11, 2011

TABLE II

PERFORMANCE STATISTICS OF THE BEST PERFORMING TECHNICAL TRADING RULE BEFORE TRANSACTION COSTS

IN THIS TABLE WE PRESENT THE PERFORMANCE OF THE BEST TECHNICAL TRADING RULE FOR EACH COUNTRY AND FOR THE ENTIRE SAMPLE PERIOD, BEFORE ADJUSTING FOR TRANSACTION COSTS. THIS TABLE REPORTS THE MEAN DAILY RETURN, THE NOMINAL *P*-VALUE, AND THREE DATA SNOOPING ADJUSTED *P*-VALUES, WHICH ARE DESCRIBED IN THE METHODOLOGY SECTION OF THIS PAPER.

Country	Best technical trading rule	Mean daily return	nominal *p*-value	RC *p*-value	SPA consistent *p*-value	SPA lower *p*-value	Country	Best technical trading rule	Mean daily return	Nominal *p*-value	RC *p*-value	SPA consistent *p*-value	SPA lower *p*-value
Argentina	ALX (0.005)	0.16%	0.0060	0.2200	0.2200	0.1540	Kuwait	EMC (20,65,0)	0.10%	0.0200	0.2500	0.2500	0.1360
Bahrain	BBA (2,0)	0.11%	0.0040	0.0280	0.0280	0.0240	Latvia	ALX (0.10)	0.12%	0.0900	0.5020	0.5020	0.4480
Botswana	EMC (15,25,0)	0.11%	0.0020	0.0160	0.0160	0.0100	Lebanon	BBA (2,0.5)	0.12%	0.0000	0.0160	0.0160	0.0100
Brazil	DMC (20,25)	0.31%	0.3340	0.9920	0.9760	0.6480	Lithuania	EMC (5,15,0)	0.22%	0.0020	0.0200	0.0200	0.0160
Bulgaria	DMC (5,40)	0.20%	0.0340	0.2880	0.2880	0.2220	Malaysia	ALX (0.005)	0.21%	0.0000	0.0000	0.0000	0.0000
Chile	BBA (2,0)	0.22%	0.0000	0.0000	0.0000	0.0000	Mexico	BBA (2,0)	0.20%	0.0000	0.0120	0.0100	0.0060
Colombia	BBA (2,0)	0.26%	0.0000	0.0640	0.0580	0.0280	Morocco	BBA (2,0)	0.19%	0.0020	0.0080	0.0080	0.0080
Czech Republic	ALX (0.005)	0.15%	0.0020	0.0280	0.0280	0.0220	Nigeria	RSI (3,0.001)	0.30%	0.0000	0.0000	0.0000	0.0000
Ecuador	REF (50,90)	0.06%	0.0120	0.2380	0.2380	0.2020	Oman	RSI (3,0.002)	0.19%	0.0000	0.0020	0.0020	0.0020
Egypt	RSI (5,0)	0.23%	0.0000	0.0020	0.0020	0.0020	Pakistan	ALX (0.005)	0.21%	0.0000	0.0040	0.0040	0.0040
Estonia	MAB (10,0.001)	0.19%	0.0020	0.0360	0.0340	0.0300	Poland	MAB (5,0.001)	0.17%	0.0000	0.0340	0.0340	0.0340
Hungary	RSI (3,0.002)	0.17%	0.0020	0.0940	0.0880	0.0580	Romania	ALX (0.005)	0.28%	0.0000	0.0080	0.0080	0.0040
India	ALX (0.005)	0.20%	0.0000	0.0000	0.0000	0.0000	Russia	MAB (3,0.002)	0.31%	0.0020	0.0360	0.0360	0.0280
Indonesia	ALX (0.005)	0.24%	0.0000	0.0000	0.0000	0.0000	South Africa	RSI (3,0.005)	0.12%	0.0080	0.3320	0.3280	0.2400
Jamaica	ALX (0.005)	0.23%	0.0000	0.0000	0.0000	0.0000	Turkey	MAB (5,0)	0.30%	0.0000	0.1120	0.1120	0.0680
Jordan	RSI (3,0.005)	0.11%	0.0000	0.0080	0.0080	0.0040	Venezuela	BBA (2,0)	0.27%	0.0000	0.0000	0.0000	0.0000
Kenya	ALX (0.005)	0.18%	0.0000	0.0000	0.0000	0.0000	Zambia	DRI (45,3)	0.11%	0.0400	0.5760	0.4820	0.3620

TABLE III

PERFORMANCE STATISTICS OF THE BEST PERFORMING TECHNICAL TRADING RULE AFTER TRANSACTION COSTS

IN THIS TABLE WE PRESENT THE PERFORMANCE OF THE BEST TECHNICAL TRADING RULE FOR EACH COUNTRY AND FOR THE ENTIRE SAMPLE PERIOD, AFTER ADJUSTING FOR TRANSACTION COSTS. THIS TABLE REPORTS THE MEAN DAILY RETURN, THE NOMINAL *P*-VALUE, AND THREE DATA SNOOPING ADJUSTED *P*-VALUES, WHICH ARE DESCRIBED IN THE METHODOLOGY SECTION OF THIS PAPER.

Country	Best technical trading rule	Mean daily return	nominal *p*-value	RC *p*-value	SPA consistent *p*-value	SPA lower *p*-value	Country	Number of observations	Mean daily return	Nominal *p*-value	RC *p*-value	SPA consistent *p*-value	SPA lower *p*-value
Argentina	ALX (0.12)	0.09%	0.1160	0.9460	0.6360	0.4820	Kuwait	EMC (25,60,0)	0.09%	0.0260	0.3900	0.1500	0.1120
Bahrain	DMC (10,40)	0.08%	0.0140	0.1780	0.0840	0.0680	Latvia	ALX (0.10)	0.11%	0.0900	0.8360	0.5540	0.3640
Botswana	EMC (20,25,0.001)	0.10%	0.0060	0.0560	0.0360	0.0320	Lebanon	EMC (25,50,0.001)	0.07%	0.0000	0.4420	0.2300	0.1600
Brazil	DMC (20,35)	0.28%	1.0000	1.0000	1.0000	1.0000	Lithuania	EMC (5,15,0)	0.17%	0.0020	0.1460	0.0840	0.0700
Bulgaria	EMC (15,45,0)	0.18%	0.0380	0.4380	0.3680	0.1980	Malaysia	EMC (15,60,0.005)	0.09%	0.0000	0.2480	0.1360	0.0940
Chile	MAB (25,0.003)	0.11%	0.0140	0.4220	0.1980	0.0880	Mexico	MAB (30,0.002)	0.09%	0.0000	1.0000	0.9500	0.6120
Colombia	ALX (0.16)	0.13%	0.2920	0.9980	0.9480	0.7080	Morocco	ALX (0.025)	0.09%	0.0020	0.9660	0.7640	0.4060
Czech Republic	EMC (10,30,0.005)	0.08%	0.0500	0.5860	0.2820	0.2200	Nigeria	ALX (0.005)	0.18%	0.0000	0.1920	0.1200	0.0820
Ecuador	REF (50,90)	0.06%	0.0100	0.3120	0.1480	0.1060	Oman	MAB (60,0)	0.14%	0.0000	0.0420	0.0280	0.0200
Egypt	EMC (15,55,0.001)	0.12%	0.0460	0.4600	0.2540	0.1740	Pakistan	MAC (4,25,0.001)	0.14%	0.0000	0.0860	0.0540	0.0360
Estonia	EMC (10,20,0.001)	0.15%	0.0220	0.3420	0.1800	0.1340	Poland	EMC (3,65,0.001)	0.10%	0.0000	0.6900	0.3160	0.2560
Hungary	EMC (20,35,0)	0.10%	0.0940	0.8820	0.5400	0.4040	Romania	ALX (0.02)	0.18%	0.0000	0.3660	0.2000	0.1460
India	EMC (2,50,0.005)	0.09%	0.1580	0.9640	0.6940	0.4540	Russia	MAC (1,20,0.02)	0.22%	0.0360	0.5500	0.3340	0.2300
Indonesia	MAC (2,35,0.005)	0.13%	0.0800	0.1640	0.0900	0.0640	South Africa	MAC (25,55,0.001)	0.05%	0.0080	1.0000	0.9520	0.6860
Jamaica	ALX (0.01)	0.15%	0.0000	0.0200	0.0160	0.0140	Turkey	ALX (0.035)	0.16%	0.0000	1.0000	0.9620	0.7620
Jordan	EMC (25,55,0)	0.05%	0.1220	0.9500	0.5880	0.4460	Venezuela	ALX (0.16)	0.11%	0.0000	0.9940	0.8180	0.5760
Kenya	ALX (0.02)	0.13%	0.0000	0.0000	0.0000	0.0000	Zambia	ALX (0.30)	0.09%	0.0400	1.0000	0.9540	0.7260

International Journal of Business, Human and Social Sciences
ISSN: 2517-9411
Vol:5, No:11, 2011

TABLE IV

SUMMARY STATISTICS OF THE BEST PERFORMING TECHNICAL TRADING RULE BEFORE TRANSACTION COSTS

THIS TABLE GIVES AN OVERVIEW OF THE SUMMARY STATISTICS OF THE BEST TECHNICAL TRADING RULE FOR EACH COUNTRY. WE REPORT THE TOTAL NUMBER OF TRADES, THE AVERAGE RETURN PER TRADE, THE AVERAGE NUMBER OF DAYS PER TRADE, AND THE HIT RATE[1] FOR THE ENTIRE SAMPLE PERIOD.. WE ALSO REPORT THESE STATISTICS FOR LONG TRADES AND SHORT TRADES SEPARATELY. THIS TABLE REPORTS THE RESULTS BEFORE INCLUDING TRANSACTION COSTS.

Country	Number of trades	Hit rate (%)	Average days per trade	Average return per trade	Number of long trades	Hit rate (%)	Average days per long trade	Average return per long trade	Number of short trades	Hit rate (%)	Average days per short trade	Average return per short trade
Argentina	1490	41%	3	0,49%	745	44%	3	0,62%	745	38%	3	0,37%
Bahrain	854	40%	3	0,25%	427	44%	3	0,28%	427	37%	2	0,22%
Botswana	50	48%	49	5,54%	25	40%	65	7,82%	25	56%	34	3,25%
Brazil	240	48%	23	6,49%	120	58%	30	13,04%	120	38%	15	-0,06%
Bulgaria	64	48%	41	7,93%	32	56%	50	10,59%	32	41%	31	5,28%
Chile	2302	49%	3	0,59%	1151	53%	3	0,78%	1151	44%	3	0,39%
Colombia	970	46%	3	0,64%	485	55%	3	0,92%	485	36%	2	0,35%
Czech Republic	1170	43%	4	0,54%	585	46%	4	0,58%	585	39%	3	0,49%
Ecuador	26	50%	120	9,61%	13	54%	105	3,99%	13	46%	134	15,22%
Egypt	948	48%	4	0,97%	474	50%	5	1,18%	474	45%	4	0,77%
Estonia	312	41%	9	1,76%	156	47%	10	2,32%	156	35%	8	1,20%
Hungary	1860	42%	3	0,46%	930	45%	3	0,73%	930	40%	3	0,30%
India	1548	45%	4	0,81%	774	49%	4	1,05%	774	41%	4	0,57%
Indonesia	1418	48%	5	1,21%	709	51%	5	1,46%	709	45%	5	0,95%
Jamaica	792	51%	8	1,80%	396	51%	8	2,31%	396	52%	8	1,30%
Jordan	1536	45%	4	0,43%	768	45%	4	0,43%	768	45%	4	0,29%
Kenya	270	43%	8	1,34%	135	41%	9	1,78%	135	44%	8	0,90%
Kuwait	50	60%	82	7,89%	25	72%	103	10,81%	25	48%	61	4,97%
Latvia	24	58%	117	13,39%	12	58%	178	18,77%	12	58%	56	8,00%
Lebanon	1252	37%	3	0,36%	626	33%	3	0,39%	626	42%	3	0,33%
Lithuania	158	51%	18	3,86%	79	53%	21	4,76%	79	48%	16	2,97%

[1] Hit Rate = Number of successful trades / Total number of trades.

TABLE IV
(CONTINUED)

Country	Number of trades	Hit rate (%)	Average days per trade	Average return per trade	Number of long trades	Hit rate (%)	Average days per long trade	Average return per long trade	Number of short trades	Hit rate (%)	Average days per short trade	Average return per short trade
Malaysia	1852	48%	4	0,89%	926	50%	5	0,99%	926	45%	4	0,80%
Mexico	1252	37%	3	0,36%	626	33%	3	0,39%	626	42%	3	0,33%
Morocco	900	44%	3	0,47%	450	51%	3	0,62%	450	37%	2	0,32%
Nigeria	716	51%	4	1,15%	358	53%	4	1,07%	358	49%	4	0,96%
Oman	940	47%	4	0,72%	470	49%	4	0,62%	470	46%	4	0,62%
Pakistan	1370	44%	4	0,88%	685	48%	5	1,09%	685	41%	4	0,67%
Poland	626	43%	5	0,83%	313	50%	5	1,00%	313	35%	4	0,66%
Romania	968	46%	4	0,98%	484	51%	4	1,20%	484	41%	3	0,76%
Russia	132	44%	3	0,76%	66	51%	4	0,10%	66	37%	3	1,42%
South Africa	1408	43%	3	0,33%	704	48%	3	0,60%	704	38%	3	0,20%
Turkey	626	43%	5	0,83%	313	50%	5	1,00%	313	35%	4	0,66%
Venezuela	1942	41%	3	0,64%	971	41%	3	0,87%	971	41%	2	0,41%
Zambia	210	49%	17	1,77%	105	56%	32	3,09%	105	42%	1	0,46%

International Journal of Business, Human and Social Sciences
ISSN: 2517-9411
Vol:5, No:11, 2011

TABLE V
SUMMARY STATISTICS OF THE BEST PERFORMING TECHNICAL TRADING RULE AFTER TRANSACTION COSTS
THIS TABLE GIVES AN OVERVIEW OF THE SUMMARY STATISTICS OF THE BEST TECHNICAL TRADING RULE FOR EACH COUNTRY. WE REPORT THE TOTAL NUMBER OF TRADES, THE AVERAGE RETURN PER TRADE, THE AVERAGE NUMBER OF DAYS PER TRADE, AND THE HIT RATE FOR THE ENTIRE SAMPLE PERIOD. WE ALSO REPORT THESE STATISTICS FOR LONG TRADES AND SHORT TRADES SEPARATELY. THIS TABLE REPORTS THE RESULTS AFTER INCLUDING TRANSACTION COSTS

Country	Number of trades	Hit rate (%)	Average days per trade	Average return per trade	Number of long trades	Hit rate (%)	Average days per long trade	Average return per long trade	Number of short trades	Hit rate (%)	Average days per short trade	Average return per short trade
Argentina	80	49%	56	6,01%	40	53%	80	8,35%	40	45%	32	3,67%
Bahrain	34	53%	60	5,72%	17	59%	74	5,89%	17	47%	45	4,12%
Botswana	22	73%	109	11,94%	11	91%	140	17,08%	11	55%	79	6,80%
Brazil	116	48%	47	13,75%	58	66%	64	27,31%	58	31%	30	0,20%
Bulgaria	52	50%	50	9,58%	26	62%	61	12,12%	26	38%	39	5,61%
Chile	276	41%	22	3,13%	138	46%	26	3,98%	138	36%	17	0,92%
Colombia	8	75%	303	40,12%	4	100%	568	73,97%	4	50%	37	3,79%
Czech Republic	118	46%	33	3,52%	59	49%	38	3,44%	59	42%	28	2,18%
Ecuador	26	42	120	8,99%	13	46%	105	3,49%	13	38%	134	14,77%
Egypt	68	47%	60	8,04%	34	50%	64	9,48%	34	44%	56	4,28%
Estonia	104	45%	26	4,58%	52	54%	31	5,17%	52	37%	21	2,37%
Hungary	14	57%	30	5,31%	7	29%	28	1,43%	7	86%	32	9,19%
India	242	40%	25	3,44%	121	45%	30	4,93%	121	35%	20	1,95%
Indonesia	190	45%	36	5,80%	95	49%	41	6,99%	95	41%	31	3,19%
Jamaica	498	45%	12	2,57%	249	47%	12	2,66%	249	43%	12	1,07%
Jordan	90	45%	63	3,51%	45	48%	70	5,73%	45	43%	57	1,67%
Kenya	214	54%	25	4,08%	107	55%	26	4,81%	107	53%	24	3,35%
Kuwait	46	63%	90	8,56%	23	78%	111	11,01%	23	48%	68	4,66%
Latvia	24	50%	117	12,56%	12	58%	178	17,94%	12	42%	56	7,24%
Lebanon	66	50%	57	3,57%	33	48%	53	3,28%	33	52%	60	2,35%
Lithuania	150	46%	19	4,02%	75	48%	21	4,14%	75	44%	16	2,28%

International Journal of Business, Human and Social Sciences
ISSN: 2517-9411
Vol:5, No:11, 2011

TABLE V
(CONTINUED)

Country	Number of trades	Hit rate (%)	Average days per trade	Average return per trade	Number of long trades	Hit rate (%)	Average days per long trade	Average return per long trade	Number of short trades	Hit rate (%)	Average days per short trade	Average return per short trade
Malaysia	42	55%	64	8,79%	21	62%	78	9,39%	21	48%	50	6,61%
Mexico	320	35%	18	2,53%	160	44%	24	3,47%	160	26%	13	0,20%
Morocco	90	43%	25	2,91%	45	58%	32	3,66%	45	29%	19	0,74%
Nigeria	428	48%	7	1,90%	214	51%	7	1,54%	214	44%	6	0,86%
Oman	58	52%	63	9,45%	29	55%	76	10,27%	29	48%	50	7,18%
Pakistan	194	48%	29	4,94%	97	49%	33	5,77%	97	46%	25	2,69%
Poland	90	36%	35	4,41%	45	40%	42	4,91%	45	31%	28	2,20%
Romania	402	47%	8	2,23%	201	51%	10	2,05%	201	43%	7	1,01%
Russia	204	46%	17	4,19%	102	48%	21	5,23%	102	44%	13	3,22%
South Africa	104	43%	68	6,16%	52	56%	78	8,58%	52	31%	58	1,91%
Turkey	702	46%	8	2,10%	351	48%	10	3,41%	351	43%	7	0,78%
Venezuela	28	64%	163	19,85%	14	71%	235	35,36%	14	57%	92	4,33%
Zambia	4	75%	898	85,89%	2	100%	1560	162,64%	2	50%	237	7,39%

TABLE VI

PERFORMANCE STATISTICS OF THE BEST PERFORMING TECHNICAL TRADING RULE DURING THE ECONOMIC CRISIS BEFORE TRANSACTION COSTS

IN THIS TABLE WE PRESENT THE PERFORMANCE OF THE BEST TECHNICAL TRADING RULE FOR EACH STOCK MARKET AND FOR THE ECONOMIC CRISIS SUBPERIOD, BEFORE ADJUSTING FOR TRANSACTION COSTS. THIS TABLE REPORTS THE MEAN DAILY RETURN, THE NOMINAL *P*-VALUE, AND THREE DATA SNOOPING ADJUSTED *P*-VALUES, WHICH ARE DESCRIBED IN THE METHODOLOGY SECTION OF THIS PAPER (NUMBER OF OBSERVATIONS: 412)

Country	Best technical trading rule	Mean daily return	nominal *p*-value	RC *p*-value	SPA consistent *p*-value	SPA lower *p*-value	Country	Best technical trading rule	Mean daily return	Nominal *p*-value	RC *p*-value	SPA consistent *p*-value	SPA lower *p*-value
Argentina	MACD (8,10,11,0)	0.30%	0.0140	0.1640	0.1640	0.1560	Kuwait	MAB (7,0)	0.29%	0.0140	0.1400	0.1400	0.1400
Bahrain	RSI (3,0.01)	0.18%	0.0020	0.0320	0.0320	0.0320	Latvia	DMC (7,60)	0.32%	0.0000	0.0020	0.0020	0.0020
Botswana	ALX (0.005)	0.21%	0.0000	0.0000	0.0000	0.0000	Lebanon	MAC (4,40,0)	0.31%	0.0040	0.0580	0.0580	0.0580
Brazil	DMC (25,35)	0.20%	0.0980	0.6740	0.6740	0.5700	Lithuania	DMC (7,15)	0.39%	0.0000	0.0000	0.0000	0.0000
Bulgaria	MAB (25,0)	0.52%	0.0020	0.0140	0.0140	0.0140	Malaysia	BBA (2,0)	0.21%	0.0000	0.1080	0.1080	0.1060
Chile	BBA (2,0)	0.29%	0.0400	0.1660	0.1640	0.1560	Mexico	EMC (2,45,0)	0.18%	0.0320	0.9680	0.4060	0.3940
Colombia	REF (40,5)	0.12%	0.0860	0.2400	0.2400	0.2400	Morocco	ALX (0.005)	0.23%	0.0140	0.2600	0.2600	0.2400
Czech Republic	MACD (18,40,11,0)	0.31%	0.0000	0.0480	0.0480	0.0480	Nigeria	RSI (4,0)	0.74%	0.0000	0.0000	0.0000	0.0000
Ecuador	ALX (0.10)	0.05%	0.0580	0.0820	0.0820	0.0800	Oman	RSI (3,0)	0.50%	0.0000	0.0640	0.0640	0.0540
Egypt	MACD (2,5,7,0)	0.51%	0.0060	0.1420	0.1420	0.1280	Pakistan	BBA (2,0)	0.35%	0.0120	0.1500	0.1500	0.1440
Estonia	MACD (6,60,7,0)	0.34%	0.0000	0.0240	0.0240	0.0240	Poland	EMC (4,5,0.001)	0.38%	0.0000	0.0160	0.0160	0.0160
Hungary	ALX (0.005)	0.32%	0.0180	0.2620	0.2620	0.2440	Romania	ALX (0.035)	0.48%	0.0020	0.1000	0.1000	0.1000
India	MACD (2,5,3,0.40)	0.33%	0.0220	0.3460	0.3440	0.3200	Russia	ALX (0.08)	0.53%	0.0120	0.3040	0.3040	0.2940
Indonesia	BBA (2,0)	0.45%	0.0040	0.6860	0.6240	0.4440	South Africa	MACD (2,5,3,0.05)	0.16%	0.0320	0.3480	0.3480	0.3300
Jamaica	REF (15,25)	0.11%	0.0180	0.1640	0.1640	0.1620	Turkey	MACD (18,20,5,0)	0.29%	0.0140	0.3600	0.3600	0.3380
Jordan	RSI (3,0)	0.34%	0.0240	0.4640	0.4640	0.4400	Venezuela	MACD (8,10,3,0.30)	0.17%	0.0500	0.3760	0.3760	0.2920
Kenya	RSI (4,0)	0.54%	0.0000	0.0000	0.0000	0.0000	Zambia	DMC (3,25)	0.29%	0.0000	0.0080	0.0080	0.0080

TABLE VII

PERFORMANCE STATISTICS OF THE BEST PERFORMING TECHNICAL TRADING RULE DURING THE ECONOMIC CRISIS AFTER TRANSACTION COSTS

IN THIS TABLE WE PRESENT THE PERFORMANCE OF THE BEST TECHNICAL TRADING RULE FOR EACH STOCK MARKET AND FOR THE ECONOMIC CRISIS SUBPERIOD, AFTER ADJUSTING FOR TRANSACTION COSTS. THIS TABLE REPORTS THE MEAN DAILY RETURN, THE NOMINAL *P*-VALUE, AND THREE DATA SNOOPING ADJUSTED *P*-VALUES, WHICH ARE DESCRIBED IN THE METHODOLOGY SECTION OF THIS PAPER (NUMBER OF OBSERVATIONS: 412).

Country	Best technical trading rule	Mean daily return	nominal *p*-value	RC *p*-value	SPA consistent *p*-value	SPA lower *p*-value	Country	Best technical trading rule	Mean daily return	Nominal *p*-value	RC *p*-value	SPA consistent *p*-value	SPA lower *p*-value
Argentina	MACD (8,10,11,0)	0.22%	0.0440	0.3240	0.3240	0.2980	Kuwait	EMC (15,45,0)	0.25%	0.0100	0.2120	0.1940	0.1600
Bahrain	MAC (25,65,0.005)	0.14%	0.0040	0.1120	0.1100	0.0940	Latvia	EMC (25,55,0)	0.30%	0.0020	0.0580	0.0580	0.0580
Botswana	ALX (0.005)	0.20%	0.0000	0.0000	0.0000	0.0000	Lebanon	MAC (4,40,0)	0.30%	0.0020	0.0620	0.0620	0.0420
Brazil	DMC (25,35)	0.17%	0.1460	0.9440	0.9300	0.7660	Lithuania	DMC (7,15)	0.35%	0.0000	0.0000	0.0000	0.0000
Bulgaria	EMC (2,50,0)	0.50%	0.0020	0.0180	0.0180	0.0160	Malaysia	DMC (7,45)	0.14%	0.0380	0.4640	0.4080	0.3200
Chile	EMC (3,15,0)	0.15%	0.0460	0.7060	0.6140	0.4380	Mexico	MAC (10,35,0.001)	0.15%	0.0940	0.7840	0.7080	0.5200
Colombia	REF (40,5)	0.11%	0.0760	0.3660	0.3460	0.2800	Morocco	ALX (0.02)	0.12%	0.0920	0.7400	0.6040	0.4540
Czech Republic	MACD (18,40,11,0)	0.27%	0.0040	0.0760	0.0760	0.0740	Nigeria	RSI (4,0.001)	0.63%	0.0000	0.0000	0.0000	0.0000
Ecuador	ALX (0.10)	0.05%	0.0560	0.5180	0.3680	0.2540	Oman	RSI (7,0.02)	0.34%	0.0080	0.1940	0.1940	0.1480
Egypt	MAB (30,0)	0.39%	0.0120	0.2240	0.2160	0.1760	Pakistan	MAC (10,30,0.001)	0.28%	0.0300	0.2580	0.1680	0.1460
Estonia	MACD (12,60,5,0)	0.29%	0.0000	0.0420	0.0420	0.0340	Poland	MAC (20,45,0.01)	0.31%	0.0100	0.1060	0.0980	0.0700
Hungary	MACD (12,15,15,0)	0.07%	0.1260	0.3580	0.3280	0.2440	Romania	EMC (2,15,0.001)	0.42%	0.0040	0.1420	0.1420	0.1120
India	MAB (35,0)	0.25%	0.0740	0.6780	0.6240	0.4800	Russia	ALX (0.08)	0.50%	0.0120	0.2840	0.2840	0.2400
Indonesia	MAC (4,45,0)	0.24%	0.0640	0.1440	0.1440	0.1300	South Africa	MAC (10,40,0.001)	0.11%	0.0920	0.7060	0.7040	0.6040
Jamaica	REF (15,25)	0.09%	0.0540	0.5880	0.5120	0.3660	Turkey	DMC (15,35)	0.24%	0.0240	0.5900	0.5700	0.4140
Jordan	EMC (25,55,0.001)	0.22%	0.0480	0.6180	0.6060	0.4360	Venezuela	DMC (20,30)	0.11%	0.1840	0.7920	0.7480	0.4920
Kenya	ALX (0.005)	0.44%	0.0000	0.0180	0.0180	0.0100	Zambia	DMC (3,25)	0.28%	0.0060	0.0240	0.0240	0.0160

TABLE VIII

SUMMARY STATISTICS OF THE BEST PERFORMING TECHNICAL TRADING RULE DURING THE ECONOMIC CRISIS BEFORE TRANSACTION COSTS

THIS TABLE GIVES AN OVERVIEW OF THE SUMMARY STATISTICS OF THE BEST TECHNICAL TRADING RULE FOR EACH COUNTRY DURING THE CRISIS SUBSAMPLE. WE REPORT THE TOTAL NUMBER OF TRADES, THE AVERAGE RETURN PER TRADE, THE AVERAGE NUMBER OF DAYS PER TRADE, AND THE HIT RATE. WE ALSO REPORT THESE STATISTICS FOR LONG TRADES AND SHORT TRADES SEPARATELY. THIS TABLE REPORTS THE RESULTS BEFORE INCLUDING TRANSACTION COSTS

Country	Number of trades	Hit rate (%)	Average days per trade	Average return per trade	Number of long trades	Hit rate (%)	Average days per long trade	Average return per long trade	Number of short trades	Hit rate (%)	Average days per short trade	Average return per short trade
Argentina	46	61%	9	2,53%	23	61%	9	1,83%	23	61%	9	3,23%
Bahrain	128	53%	3	0,61%	64	48%	3	1,80%	64	58%	3	0,98%
Botswana	8	88%	52	10,15%	4	75%	36	5,62%	4	100%	67	14,67%
Brazil	14	57%	29	5,97%	7	71%	31	4,50%	7	43%	28	7,44%
Bulgaria	16	56%	26	13,22%	8	38%	15	3,18%	8	75%	37	23,26%
Chile	156	53%	3	0,76%	78	62%	3	0,84%	78	44%	3	0,68%
Colombia	6	33%	68	0,83%	3	33%	71	0,16%	3	33%	65	1,54%
Czech Republic	24	55%	17	4,05%	12	45%	16	1,23%	12	64%	18	6,87%
Ecuador	2	50%	206	10,34%	1	0%	93	-5,15%	1	100%	319	15,49%
Egypt	98	55%	4	2,11%	49	59%	4	1,62%	49	51%	4	2,60%
Estonia	38	55%	11	3,61%	19	42%	11	1,33%	19	68%	10	5,89%
Hungary	130	51%	3	1,06%	65	43%	3	0,68%	65	58%	3	1,45%
India	100	55%	4	1,38%	50	56%	4	1,19%	50	54%	4	1,56%
Indonesia	170	49%	3	1,09%	85	49%	3	0,96%	85	49%	3	1,21%
Jamaica	6	83%	66	6,86%	3	67%	58	3,58%	3	100%	74	10,15%
Jordan	122	37%	3	1,13%	61	31%	4	2,66%	61	42%	3	1,24%
Kenya	84	57%	5	2,65%	42	57%	4	4,44%	42	57%	6	3,25%
Kuwait	62	48%	7	1,97%	31	48%	7	1,13%	31	48%	7	2,81%
Latvia	2	100%	206	61,35%	1	100%	46	12,57%	1	100%	366	110,14%
Lebanon	4	75%	103	32,86%	2	100%	78	30,51%	2	50%	129	35,21%
Lithuania	18	67%	23	8,42%	9	67%	17	2,65%	9	67%	29	14,18%

TABLE VIII
(CONTINUED)

Country	Number of trades	Hit rate (%)	Average days per trade	Average return per trade	Number of long trades	Hit rate (%)	Average days per long trade	Average return per long trade	Number of short trades	Hit rate (%)	Average days per short trade	Average return per short trade
Malaysia	180	44%	2	0,48%	90	38%	2	0,34%	90	51%	3	0,61%
Mexico	22	27%	19	2,90%	11	36%	17	1,96%	11	18%	21	3,84%
Morocco	84	46%	5	1,08%	42	45%	5	0,97%	42	48%	5	1,18%
Nigeria	64	66%	6	4,76%	32	63%	5	6,79%	32	69%	8	5,85%
Oman	116	56%	4	1,79%	58	55%	4	3,17%	58	57%	3	2,14%
Pakistan	150	43%	3	0,98%	75	40%	3	0,54%	75	45%	3	1,42%
Poland	60	63%	6	3,05%	30	71%	6	2,46%	30	54%	6	3,64%
Romania	44	52%	9	4,52%	22	45%	9	2,35%	22	59%	10	6,69%
Russia	18	67%	23	12,03%	9	67%	27	7,58%	9	67%	18	16,49%
South Africa	142	49%	3	0,45%	71	42%	3	0,18%	71	55%	3	0,71%
Turkey	64	58%	6	1,99%	32	47%	7	1,38%	32	69%	6	2,59%
Venezuela	52	48%	8	1,14%	26	46%	8	1,41%	26	50%	8	0,88%
Zambia	10	80%	41	11,94%	5	100%	29	9,40%	5	60%	53	14,48%

TABLE IX

SUMMARY STATISTICS OF THE BEST PERFORMING TECHNICAL TRADING RULE DURING THE ECONOMIC CRISIS AFTER TRANSACTION COSTS

THIS TABLE GIVES AN OVERVIEW OF THE SUMMARY STATISTICS OF THE BEST TECHNICAL TRADING RULE FOR EACH COUNTRY DURING THE CRISIS SUBSAMPLE. WE REPORT THE TOTAL NUMBER OF TRADES, THE AVERAGE RETURN PER TRADE, THE AVERAGE NUMBER OF DAYS PER TRADE, AND THE HIT RATE. WE ALSO REPORT THESE STATISTICS FOR LONG TRADES AND SHORT TRADES SEPARATELY. THIS TABLE REPORTS THE RESULTS AFTER INCLUDING TRANSACTION costs.

Country	Number of trades	Hit rate (%)	Average days per trade	Average return per trade	Number of long trades	Hit rate (%)	Average days per long trade	Average return per long trade	Number of short trades	Hit rate (%)	Average days per short trade	Average return per short trade
Argentina	46	57%	9	1,70%	23	52%	9	1,03%	23	61%	9	2,49%
Bahrain	4	75%	91	14,79%	2	100%	82	4,19%	2	50%	101	25,48%
Botswana	8	75%	52	9,44%	4	50%	36	5,01%	4	100%	67	14,06%
Brazil	14	57%	29	5,08%	7	71%	31	3,71%	7	43%	28	6,69%
Bulgaria	6	67%	69	34,20%	3	33%	29	7,57%	3	100%	108	60,78%
Chile	156	53%	3	0,02%	78	62%	3	0,12%	78	44%	3	0,01%
Colombia	6	33%	68	0,57%	3	33%	71	0,06%	3	33%	65	1,12%
Czech Republic	24	38%	17	3,28%	12	33%	16	0,54%	12	42%	18	6,23%
Ecuador	2	50%	206	9,22%	1	0%	93	-5,51%	1	100%	319	14,88%
Egypt	10	90%	41	14,82%	5	100%	37	10,21%	5	80%	46	19,71%
Estonia	26	54%	16	4,66%	13	46%	16	1,37%	13	62%	16	8,07%
Hungary	30	53%	14	3,54%	15	47%	13	1,90%	15	60%	14	5,25%
India	18	44%	23	5,19%	9	44%	21	3,36%	9	44%	25	7,17%
Indonesia	170	47%	3	0,38%	85	47%	3	0,30%	85	47%	3	0,58%
Jamaica	6	83%	66	5,86%	3	67%	58	2,76%	3	100%	74	9,07%
Jordan	4	100%	102	22,02%	2	100%	116	17,01%	2	100%	88	27,11%
Kenya	58	60%	7	3,16%	29	62%	6	2,42%	29	59%	8	3,99%
Kuwait	4	75%	103	27,81%	2	50%	86	14,72%	2	100%	121	41,09%
Latvia	10	50%	41	9,35%	5	20%	14	-0,41%	5	80%	69	19,20%
Lebanon	4	75%	101	31,65%	2	100%	78	29,91%	2	50%	124	33,57%
Lithuania	18	56%	23	7,57%	9	56%	17	1,92%	9	56%	29	13,44%

TABLE IX
(CONTINUED)

Country	Number of trades	Hit rate (%)	Average days per trade	Average return per trade	Number of long trades	Hit rate (%)	Average days per long trade	Average return per long trade	Number of short trades	Hit rate (%)	Average days per short trade	Average return per short trade
Malaysia	10	50%	41	2,77%	5	80%	32	-0,01%	5	20%	50	5,67%
Mexico	10	70%	41	6,62%	5	80%	37	4,39%	5	60%	44	9,10%
Morocco	26	54%	16	2,02%	13	54%	19	1,71%	13	54%	13	2,42%
Nigeria	62	66%	7	4,22%	31	65%	5	6,31%	31	68%	8	5,40%
Oman	64	59%	6	2,32%	32	60%	6	-1,34%	32	57%	6	2,99%
Pakistan	14	79%	5	3,60%	7	57%	3	0,33%	7	100%	6	6,93%
Poland	4	100%	91	29,25%	2	100%	61	21,72%	2	100%	121	36,88%
Romania	26	46%	16	6,71%	13	42%	13	3,13%	13	50%	18	10,39%
Russia	18	67%	23	11,34%	9	67%	27	6,96%	9	67%	18	15,81%
South Africa	10	70%	41	4,59%	5	80%	35	1,48%	5	60%	47	7,85%
Turkey	12	67%	34	8,57%	6	50%	28	5,35%	6	83%	40	11,86%
Venezuela	8	75%	52	4,29%	4	75%	51	6,04%	4	75%	52	2,94%
Zambia	10	60%	41	11,30%	5	60%	29	8,78%	5	60%	53	14,01%

Appendix A

Technical Trading Systems: overview

	Trading System	***Trading Signals***	***Parameters***	***Values***	***# rules***
	Moving Averages				
1.	Simple Moving Average with band (MAB)	When the closing climbs above an upper band of a moving average, the investor takes a long position. When the closing price falls below a lower band of a moving average, the investor takes a short position. The position is held until the closing price crosses the moving average.	n = number of days in a MA $b(\%)$ = percentage band around the MA	n = [3, 5, 7, 10, 15, 20, 25, 30, 35, 40, 45, 50, 55, 60, 65] $b(\%)$ = [0, 0.1, 0.3, 0.5, 1, 1.5, 2, 2.5, 3, 3.5, 4, 4.5, 5, 5.5, 6]	225
2.	Dual Moving Average Crossover (DMC)	When a short-term moving average (STMA) climbs above a long-term moving average (LTMA), the investor takes a long position. When a STMA falls below a LTMA, the investor takes a short position. In this system, the investor is always in the market.	s = number of days in a STMA l = number of days in a LTMA	s = [1, 2, 3, 4, 5, 7, 10, 15, 20, 25] l = [5, 10, 15, 20, 25, 30, 35, 40, 45, 50, 55, 60, 65]	88
3.	Moving Average Crossover (MAC)	When a short-term moving average (STMA) climbs above an upper band of a long-term moving average (LTMA), the investor takes a long position. When a STMA falls below a lower band of an LTMA, the investor takes a short position. The position is held until a STMA crosses a LTMA.	s = number of days in a STMA l = number of days in a LTMA $b(\%)$ = percentage band around an LTMA	s = [1, 2, 3, 4, 5, 7, 10, 15, 20, 25] l = [5, 10, 15, 20, 25, 30, 35, 40, 45, 50, 55, 60, 65] $b(\%)$ = [0, 0.1, 0.5, 1, 1.5, 2, 3, 4, 5]	1026
4.	Exponential Moving Average Crossover (EMC)	The trading mechanism of the EMC is comparable to the MAC system, except that this method utilizes exponential moving averages.	s = number of days in a STMA l = number of days in a LTMA $b(\%)$ = percentage band around an LTMA	s = [2, 3, 4, 5, 7, 10, 15, 20, 25], l = [5, 10, 15, 20, 25, 30, 35, 40, 45, 50, 55, 60, 65], $b(\%)$ = [0, 0.1, 0.5, 1, 1.5, 2, 3, 4, 5]	909
5.	Moving Average Convergence-Divergence (MACD)	The MACD line indicates the difference between a short-term and a long-term exponential moving average. The signal line is an exponential moving average of the MACD line. When the MACD line climbs above an upper band of the signal line, the investor takes a long position. When the MACD line falls below a lower band of the signal line, the investor takes a short position. The positions are held until the MACD line crosses the signal line.	s = number of days in a STEMA l = number of days in a LTEMA n = numbers of days in the signal line $b(\%)$ = percentage band around the signal line	s = [2, 4, 6, 8, 10, 12, 14, 16, 18] l = [5, 10, 15, 20, 25, 30, 40, 50, 60] n = [3, 5, 7, 9, 11, 13, 15, 17, 19, 21, 23, 25] $b(\%)$ = [0, 0.1, 0.5, 1, 1.5, 2, 3, 4, 5]	7884

	Trading System	Trading Rules	Parameters	Values	# rules
	Channel Breakouts (support & resistance, trading range breakout)				
6.	Outside Price Channel (CHL)	When a closing price is higher than an upper band around the highest price in a channel length, the investor takes a long position. When a closing price is lower than a lower band around the lowest price in a channel length, the investor takes a short position. The positions are held until the closing price crosses the lowest / highest price in the time interval.	n = number of days in a time interval b(%) = percentage band around the signal line	n = [2, 3, 5, 7, 10, 15, 20, 25, 30, 35, 40, 45, 50, 55, 60, 65] b(%) = [0, 0.1, 0.5, 1, 1.5, 2, 3]	112
7.	Bollinger Bands (BBA)	When a closing price is higher than an upper band above a moving average (moving average + z*stdv), the investor takes a long position. When a closing price is lower than a lower band below a moving average (moving average - z*stdv), the investor takes a short position. The positions are held until a closing price crosses the moving average.	n = number of days in the moving average z = multiplicator	n = [2, 3, 5, 7, 10, 15, 20, 25, 30, 35, 40, 45, 50, 55, 60, 65] z = [0, 0.5, 1, 1.5, 2, 2.5, 3]	112
	Momentum Oscillator Rules				
8.	Relative Strength Index (RSI)	The RS is measured dividing an average upward price change by an average downward price change, and trading signals are generated by comparing the RSI to predetermined entry thresholds.	n = number of days used to calculate the RS et = predetermined entry thresholds	n = [3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18] et = [6, 8, 10, 12, 14, 16, 18, 20, 22, 24, 26, 28, 30, 32, 34, 36, 38, 40, 42, 44]	320
9.	Directional Indicator (DRI)	The DI measures a percentage value of a net price change (NPC) relative to a sum of absolute daily price changes (TPC) for a given time period. When a DI value is equal to or higher than a predetermined entry threshold, the investor takes a long position. When a DI value is lower than a predetermined entry threshold, the investor takes a short position. Positions are held until a DI value crossing a zero value.	n = number of days used to calculate the DI et = predetermined entry thresholds	n = [5, 10, 15, 20, 25, 30, 35, 40, 45, 50, 55, 60, 65] et = [3, 6, 9, 12, 15, 18, 21, 24, 27, 30, 33, 36, 39, 42, 45, 48, 51, 54, 57, 60, 63, 66, 69, 72, 75, 78, 81, 84, 87, 90]	390
10.	Refrence Deviation (REF)	This system uses a Moving Average as refrence point. A long (short) signal is generated when a Reference Index (RI) value is greater (less) than a predetermined positive (negative) entry threshold. The long (short) position is liquidated when a RI value is less (greater) than zero.	n = number of days used to calculate the RI et = predetermined entry thresholds	n = [5, 10, 15, 20, 25, 30, 35, 40, 45, 50] (10 values) et = [5, 10, 15, 20, 25, 30, 35, 40, 45, 50, 55, 60, 65, 70, 75, 80, 85, 90] (18 values)	180

	Trading System	Trading Rules	Parameters	Values	# rules
11.	Williams % R (WR)	When a closing price is higher than an upper threshold value, the investor takes a long position. When a closing price is lower than a lower threshold value, the investor takes a short position. Positions are held until the closing price crosses the mean of the upper and lower threshold.	*n* = number of days to calculate WR *etu* = upper threshold value *etl* = lower threshold value	*n* = [5, 10, 15, 20, 25, 30, 35, 40, 45, 50] *etu* = [-5, -10, -15, -20] *etl* = [-95, -90, -85, -80]	40
12.	Stochastic Oscillator (STO)	When a closing price is higher than an upper threshold value, the investor takes a long position. When a closing price is lower than a lower threshold value, the investor takes a short position. The positions are held until the closing price crosses a 3-days moving average.	*n* = number of days to calculate STO *etu* = upper threshold value *etl* = lower threshold value	*n* = [5, 10, 15, 20, 25, 30, 35, 40, 45, 50] *etl* = [5, 10, 15, 20] *etu* = [95, 90, 85, 80]	40
	Filter Rules				
13.	Alexander's Filter Rule (ALX)	When a closing price risies by x% above its most recent low, the investor takes a long position. When a closing price x% below its most recent high, the investor takes a short position. In this system, the investor is always in the market.	*x*(%) = change in stock price required to initiate a position	*x*(%) = [0.5, 1, 1.5, 2, 2.5, 3, 3.5, 4, 4.5, 5, 6, 7, 8, 9, 10, 12, 14, 16, 18, 20, 25, 30, 40, 50]	24

Stefaan Pauwels. Department of Financial Economics, Ghent Univeristy, Ghent University, Woodrow Wilsonplein 5D (phone: +32498676446; e-mail: stefaan.pauwels@ugent.be).
Koen Inghelbrecht, Department of Financial Economics, Ghent Univeristy, Ghent University, Woodrow Wilsonplein 5D (e-mail: koen.inghelbrecht@ugent.be).
Dries Heyman, Department of Financial Economics, Ghent Univeristy, Ghent University, Woodrow Wilsonplein 5D (e-mail: dries.heyman@ugent.be).
Pieter Marius, Financial Data Management, Dexia (e-mail:npieter.marius@dexia.com)