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Emerging Markets Queries in Finance and Business

The sensitivity of moving average trading rules performance with respect to methodological assumptions

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Abstract

The question whether the tools and methods characterizing technical analysis can lead to superior performances when it comes to forecast the future evolution of speculative prices (mainly stock prices) represents a matter of permanent debate in the specialized literature. Various surveys show long term equilibrium between the number of empirical studies that confirm these superior capacities and those failing to do so. In the same time, it is suggested that a possible explanation for these heterogeneity resides in the various methodological approaches when testing technical analysis rules. It seems that the subjective choices of the parameters can bias substantially any empirical results through the negative effects of data mining. The paper's objective is to test the sensitivity of the returns generated through the use of the dual moving average crossover rule with respect to the dimension of the investment decision space and the moment in which the investors do the actual trading suggested by the rule. Based on a price of 2,942 observations characterizing the Bucharest Stock Exchange, we ran simulations for 5,670 different trading rules and we found that particular approaches of the trading rule consistently leads to different results, approaches which are more or less prone to boost the rule's profitability. For example, using a two element space of investment decision will always outperform a three element one mainly because of the heavy trading commission fees generated by more frequently changing the investment exposures. We also considered the impact of the trading commissions when evaluating the total returns and that of the net interest that can be earned through borrowing and lending at a differentiated cash rate (namely ROBOR-3M and ROBID-3M).

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Keywords: technical analysis, moving averages, trading rules, weak form market efficiency

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1. Introduction

The methods and tools unified under the concept of technical analysis (henceforth, TA) constitute an attractive and relatively cheap way to fundament a large panel of financial investment and trading decisions. This fact can be easily checked even by only observing daily activities in any brokerage or investment company across the globe. The success with which TA was accepted in the investment industry is due mainly to the fact that TA's tools are built on (seemingly) highly intuitive and logic rationales applied on different concepts specific to the industry (speculative prices, trading volumes, sentiment indices and so on). And even more relevant for this success is the visual representations that turn abstract rationales and relations between variables into something easy and enjoyable to see and analyze. And hence the other names under which we can find TA in practice and in the literature: chartist analysis, graphical analysis.

One of the major difference between technical and fundamental analysis reside in the fact that TA does not question in any way why we have certain price or volume patterns and that is because TA implicitly assumes that all the relevant and even irrelevant information are already processed by the investors and incorporated in the price through the constant equilibrium between supply and demand in markets. In this way, the market is being credited as the (only) relevant source of information. Since TA does not explicitly assumes a strict rational behavior characterizing the investors manifestations of irrational exuberance are allowed as equally relevant bits of data when an investment decision is sought for. Thus, we can easily identify the market primordial role in this process, fact which can be easily proved by frequently circulating sayings such "The market is always right".

Finally, TA receives usually a warm welcome from the persons entering the financial investment field for the first time because of its accessibility and a lesser steep learning curve. The fact that only after a few reading/learning sessions, a beginner has the impression that is doing something professional, in a rigorous technical way can boosts its confidence in its decision making and further stimulate its efforts. Sometimes, people are even mesmerized by the intrinsic relations that take place in the philosophy of technical analysis. Beliefs in immutable laws of nature, patterns that inextricably follow preset behaviors can bias the rationales towards the astrological and mystical. To this regard we can quote the "Elliot Wave Theory" as a major responsible for these unexpected consequences of investment analysis.

TA's success in the investment industry is heavily diminished when observing it in the academic field since there are lots of studies in which is denied both on theoretical ground and empirical findings. However, the verdict is not homogenous since there is numerous papers as well which reveals TA's hidden capacities in matters of price forecasting. One of the corner-stone papers in this category is (Brock et al, 1992) which gave a methodology extensively followed afterwards by studies dedicated to this area.

But strictly from a theoretical point of view, TA is usually considered by the academics as "less than fully rational" or "second best form of analysis" explicitly because it doesn't rests on solid theoretical grounds but only on intuitive empirical observations transformed into laws. An early but strong rejection even today was given by Paul Samuelson who stated that: "There is no way of making an expected profit by extrapolating past changes, by chart or any other esoteric devices of magic or mathematics …". Anyway, the fact that TA still receives a substantial share of attention from both academics and the industry constitutes a strong argument for its role.

In their efforts to explain the somehow unexpected positive abnormal returns that are generated sometimes by following TA's tools, academics have isolated several arguments. First, as highlighted in (Jensen, 1978) the Efficient Market Hypothesis can be consistent with these abnormal profits but only up to transaction costs. In other words, even if we observe pure super-profits when applying TA's tools this is only because we do not fully considered the effect of different transactions costs like brokerage commission fees, bid-ask spreads, electronic money transfers fees and so on.

Another possible explanation for the departure of prices from their fundamental-rational trajectories is the manifestation of positive feedback investors (investors which use extensively extrapolations of past evolutions in order to derive their price forecasts), a phenomenon documented in (DeLong and Shleiffer, 1990). Additionally, for explaining different episodes of persistence in stock prices, the short-term and long term price reversals were also cited as relevant.

One major problem that affects the robustness of an empirical study testing the profitability of TA rules is the data mining or data snooping phenomenon. By running subjectively chosen trading rules on subjectively chosen price samples there is a substantial risk for finding irrelevant abnormal profits since they are so dependent on the methodological inputs. Almost for certain, this is also the reason why we have a historical divergence between empirical findings supporting and rejecting TA' superior forecast abilities. The literature has suggested several solutions to reduce/eliminate the data mining effect like using longer samples of prices and/or volumes, a large number of trading rules, a special emphasis on out-of-sample profitability tests or specially built technical solution like the reality check test developed in (White, 2000).

A recent literature summary of this topic made in (Park and Irwin, 2007) showed that from a total of 95 studies, 56 supported TA's superior forecast capacities while 39 infirmed it or generated mixed results. However, as the authors underlined, the testing procedures are usually negatively affected by methodological deficiencies that should be addressed with priority in the future.

Although TA comprises a large array of tools one of its simplest but most frequently used is the moving average trading rule. Its concept lies in the relative position of two moving averages (henceforth, MA) that smooth in different degrees the price evolution. When the short term MA crosses and surpasses the long term MA a buy signal is generated since more recent price evolutions suggest an upward trend; similarly, a reverse crossing will generate a sell signal. Without being a general rule, the MA are computed as simple averages since exponential ones tend to lead to similar results as documented by (Mitra, 2011) .

However, as simple as it is, the robustness of the results generated by a MA trading rule can suffer from the lack of objectivity in setting the dimensions for both the short and the long term moving average. Since different combinations between these parameters can lead to significantly different results in terms of returns there is no guarantee that a positive abnormal return supports a superior performance of the MA trading rule. Moreover, there is a third parameter in the design of MA rules (the filter), introduced in order to control the generation of false signals or whipsaws as they are also called. Technically, the filter sets a minimal band for the differences between the two MA that should be surpassed by any crossing in order to be significant enough to trigger a new signal. Again there is no specific rule about what values to use within a MA rule so this add another dose of subjectivity to any empirical study.

The objective of this paper is to test the sensitivity in the performance of moving average trading rules when we control for methodological assumptions. In section 2 we present a technical description of the moving average dual crossover rule and the two methodological parameters that we will control. Section 3 describes the data and the set of MA trading rules used and discusses the results of the simulations for buy, sell and total returns generated by the rules. Finally, section 3 concludes and identifies future research paths.

2. The moving average dual crossover rule

Generally, moving averages are used as a smoothing instrument in time series analysis, area from which they were introduced also in the practice of speculative prices forecasting. In the beginning, a moving average of various dimensions (n=5, 10, 20, 50 and so on) was plotted against the price series in order to get an idea of the ongoing trends. As it is obvious, shorter moving averages (n=5, 10) will follow more closely the price evolution with higher smoothing degrees being obtained by increasing n. Based on the relative dynamics of the price itself and the moving averages the following trading rules were developed: if the price series crosses the moving average from bellow a buy signal is generated since the recent evolutions puts the price on new upward trend. Conversely, if the price crosses the moving average from above a sell signal is generated. The length of the period of time during which the newly generated signal is maintained can be a priori fixed like in the fixed moving average approach (FMA) or variable, until a different signal is generated (variable moving average, VMA).

Very soon, the idea of combining the dynamics of two moving averages with different dimensions into one analysis instrument was leading to the development of the dual moving average crossover rule. However, there were no specific values recommended for the two averages nor for the later added filter this being the main reason for the large variety of combinations of these parameters that we can find in practice. We therefore define the dual crossover trading rule in a general manner.

A moving average dual crossover rule is characterized by a parameter vector b=(s, l, f, d) where:

- s and l represent the lags corresponding to the short and long moving averages (l>s);
- f is the filter value used to reduce the incidence of false signals ($f \geqslant 0$);
- d controls for the moment in which the investor implements the position that is indicated by the generated signal (d=0 means that trading is done in the same moment in which the signal is generated; d=1 delays the actual trading to the next trading session closing price).

In the existing literature there is no general consensus whether d should be set to 0 or 1, both approaches being represented in the empirical studies. Some authors suggest that d=0 or d=1 is not really a relevant topic after all the generated results being very similar. In our opinion, d=0 is not reflecting the real trading conditions available for the investors. If the investor wait until the market closes in order to get an updated status/signal from the dual crossover rule she cannot implement the corresponding trade in the same session because the first actual opportunity comes only at the opening of the next session. But since the studies only employ closing prices, the first opportunity to trade is the closing price of the next trading session.

Another variable that can affect the results of running tests for the MA trading rules is the space of investment decisions, symbolized through Ω. Most of the empirical work in this field is done using a two element Ω composed of buy and sell signals while other papers use a three element Ω, including a neutral exposure. Since the two choices would lead to different results we will investigate the impact of Ω on the MA trading rule's generated returns. As trading strategy, we use the so called double or out strategy stating that during buy periods the investor borrows money at the cash rate, a sum equal to its original capital, and thus invests a double amount in the risky asset. During sell exposures, everything is sold, the borrowed capital is return and the remaining amount is deposited at the cash rate.

3. Data and results

Our price sample consists of daily closing prices for the BET-C index, a composite index that mimics the market portfolio characterizing Bucharest Stock Exchange. The sample contains 2,942 observations recorded between 3.01.2002 and 12.11.2013 and it was obtained from the database of a local brokerage company. Regarding the MA trading rules that we tested we allow the integer parameters s and l to vary in the interval [1, 10] and [2, 100] respectively. The filter also varies in the [0%, 5%] interval taking only integer values leading thus to a universe of 5,670 trading rules. In carrying out the trades we assumed a relatively conservative one-way commission fee of 0.15% which is available usually to institutional and specialized investors. We use a differentiated cash rate for borrowing (ROBOR-3M) and depositing money (ROBID-3M), both interest series being extracted from the National Bank of Romania public database.

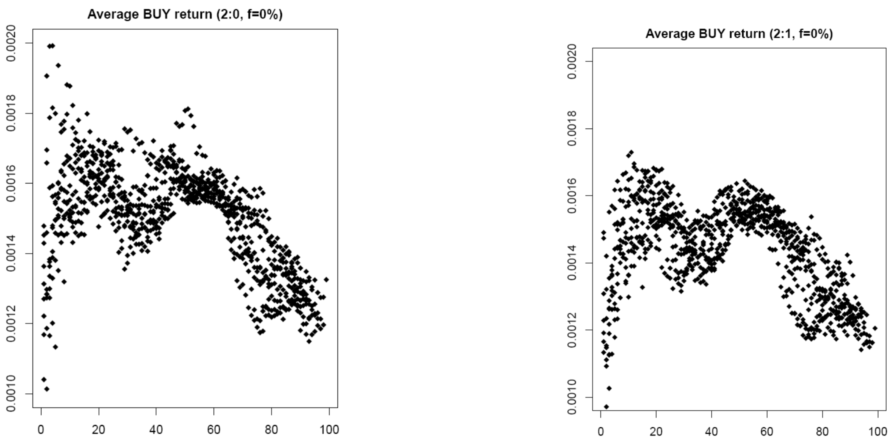

Fig. 1. (a) (d=0) numerous high positive returns; (b) returns that cannot be found when real trading conditions are imposed (d=1)

In figures 1a and 1b, we see that the use of d=0 or d=1 makes a noticeable difference in terms of average buy returns for the strategies analyzed. In figure 1a (d=0) we see numerous high positive returns in the second quadrant, returns that cannot be found when real trading conditions are imposed (figure 1b, d=1). However, these differences between the two methodological approaches tend to disappear when positive filters are used (appendices 1a and 1b). In the same time, the shape of the returns conditioned by the difference between the long and the short term moving average dimension (l-s) is stable showing that d doesn't alter the structure of the generated returns.

As we can check in appendices 2a and 2b, there is no significant difference between the average buy returns condition by the type of the investment space Ω when using a null filter. However, the conclusion radically changes when positive filters are introduces as it can be easily noticed in figures 2a and 2b. The same holds also when we vary d (appendices 3a and 3b).

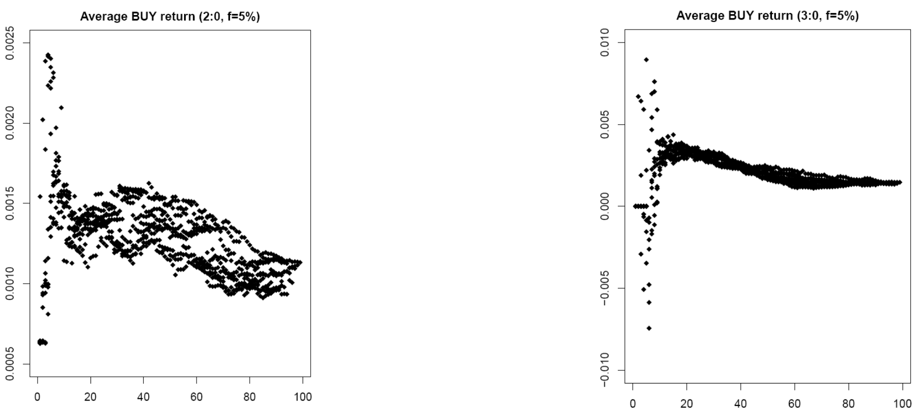

Fig. 2. (a); (b) The average buy returns condition by the type of the investment space Ω when using a null filter

The average sell return is lower when d=0 compared with the case in which d=1 when a null filter is used (figures 3a and 3b). Again, this means that using ideal trading conditions (d=0) leads to superior performances but these cannot be replicated in practice. Also, when we use positive filters this difference tends to disappear, thus rendering the d parameter irrelevant as already suggested by some studies (appendices 4a, 4b). Also, when controlling for the type of investment space Ω, there is no significant differences as it can be seen in appendices 5a, 5b. However, the differences between Ω=2 and Ω=3 become significant when nonzero filters are used.

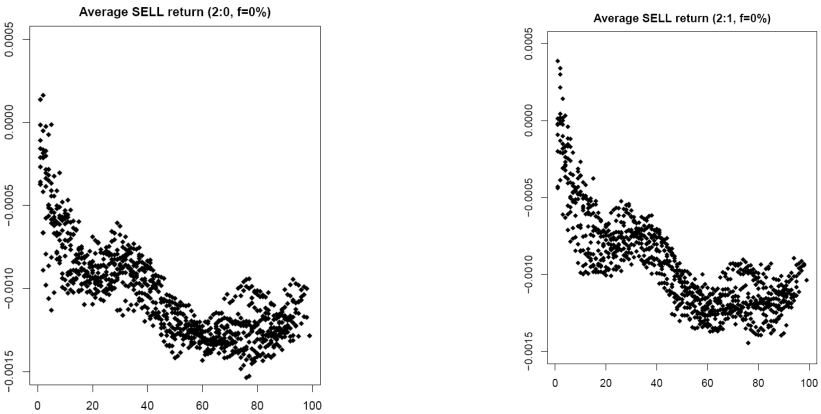

Fig. 3. (a); (b) d=0 compared with the case in which d=1 when a null filter is used

Figure 4 clearly shows that for our sample, the average sell return is substantially lower for the Ω=3 case meaning that introducing a third investment state (neuter) can improve the overall performance of the trading rule but only when this is accompanied by adequate filters that prevent an inefficient generation of signals (leading to high transaction costs that lowers the overall performance). Introducing d as a variable does not change this finding (appendices 6a, 6b).

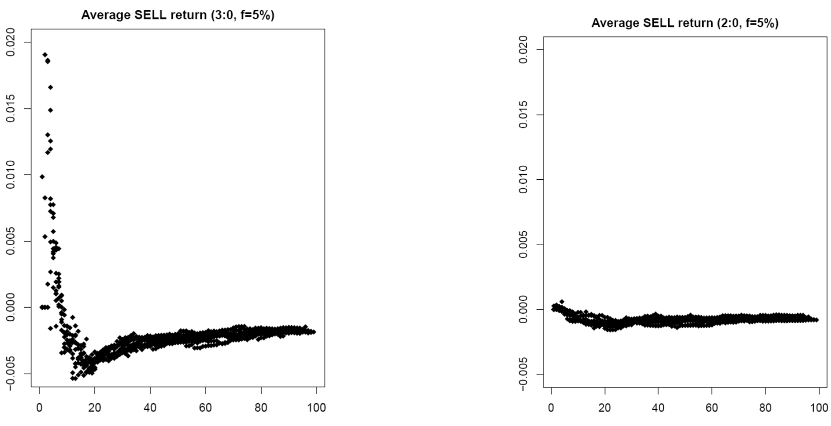

Fig. 4. (a); (b) The average sell return is substantially lower for the Ω=3

The two suggestive plots from Figure 5 shows the average sell returns when Ω=2 and Ω=3, both cases with d=1, that being the scenario that best represents real trading conditions. The frontal horizontal axis depicts the difference between the dimension of the long and the short term moving average, considered here as a relevant explanatory factor. The second horizontal axis represents the filter values, again considered to be a relevant explanatory factor. First, we observe in both cases a similar pattern of the average sell return suggesting similar behavior of sell returns with respect to the two factors: they tend to decrease for larger differences between l and s; and they tend to increase for larger filters maybe because in those cases not all trading opportunities are exploited.

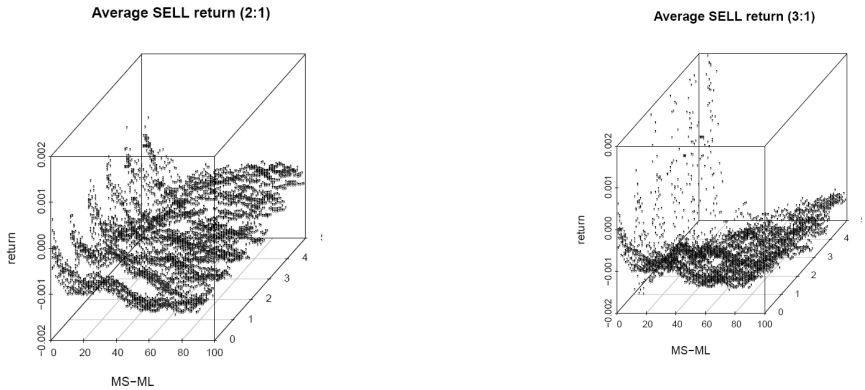

Fig. 5. (a); (b) The average sell returns when Ω=2 and Ω=3, both cases with d=1

The differences that we observed in the case of both buy and sell returns are even more visible when we look at the total return plot in Figure 6 (a, b). When a three element investment decision space is used the generated results are more compact suggesting lesser variance when we set the dimension of the short and long moving average. It therefore seems that in the case Ω=2 the subjectivity in choosing the parameters has a more substantial impact. Also, for smaller differences l-s, the resulting return is significantly less for the Ω=3 case compared to the Ω=2 case. Overall, the Ω=2 case seems to generate higher returns dominating those obtained when the neutral state is introduced.

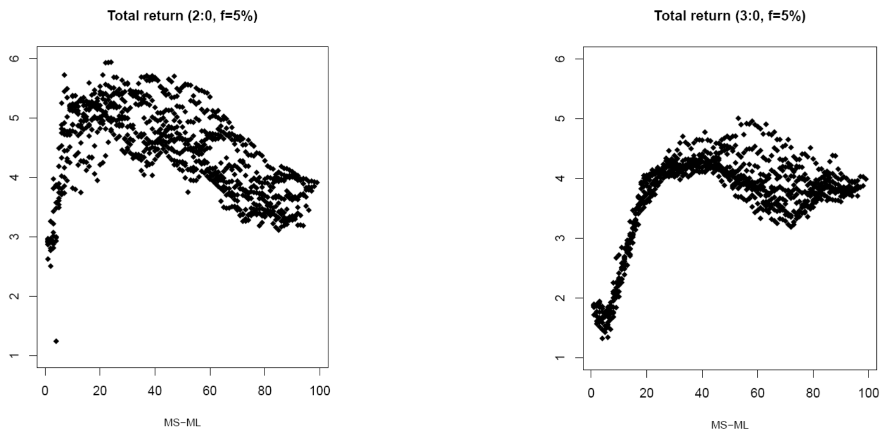

Fig. 6. (a); (b) The average sell returns when Ω=2 and Ω=3, both cases with d=1

Some interesting observations regarding the influence of the filter on the MA trading rules can be made also by looking at the average returns in Table 1. First, using d=1 constantly lowers the average buy returns regardless of the type of the investment space proving once again that d=0 is not a conservative approach when testing the TA's efficacy (in the case of the average sell returns the rules' performance is also superior when d=0). Secondly, increasing the filter improves the performance of three element investment space by avoiding some of the false signals which are more probable in this case (we have more possibilities for a change in investment exposure). But this increase of the filter has an inverse effect on the Ω=2 case. Finally, when we compared the average neutral return, possible only for the Ω=3 case, the differences generated by the parameter d seem to be insignificant.

As a general result, we can notice that the highest performance is obtained when we use Ω=3 and d=0. Therefore, when an empirical study uses this particular combination, there is a strong bias towards finding positive evidence for TA's superior forecasting capacities.

Table 1. Moving average trading rules - average return statistics

	Average buy return				Average sell return				Neutral return	
%	20	21	30	31	20	21	30	31	30	31
f	0.136	0.131	0.173	0.162	-0.092	-0.085	-0.154	-0.142	0.046	0.048
f=0	0.150	0.143	0.150	0.143	-0.104	-0.093	-0.104	-0.093	0.000	0.000
f=1	0.141	0.135	0.165	0.154	-0.094	-0.084	-0.136	-0.122	0.057	0.057
f=2	0.134	0.129	0.175	0.164	-0.093	-0.085	-0.154	-0.141	0.050	0.053
f=3	0.132	0.129	0.180	0.165	-0.100	-0.093	-0.160	-0.146	0.052	0.053
f=4	0.130	0.127	0.178	0.174	-0.090	-0.085	-0.185	-0.173	0.058	0.060
f=5	0.127	0.124	0.188	0.174	-0.075	-0.070	-0.186	-0.176	0.062	0.063

A synthetic impact of the two variables, Ω and d, on the profitability of MA trading rules can be drawn from Table 2. Compared with the individual returns (buy, sell, neutral), the total return comprises also the effect of transaction costs through the brokerage commission fee and the net interest (both variables are expressed in terms of returns). As expected, the Ω=3 case implies more commissions fees since the introduction of a third neutral investment state will increase the trading frequency.

Table 2. Moving average trading rules – average total return statistics

	1a. Average total return					2b. Commissions and net interest			
%	20	21	30	31	%	20	21	30	31
f	4.71	4.56	4.35	4.23	Total commission	-0.133	-0.133	-0.198	-0.1983
f=0	4.94	4.67	4.96	4.71	Net interest	-0.281	-0.28	-0.185	-0.1845
f=1	4.81	4.59	4.77	4.60					
f=2	4.71	4.55	4.49	4.36					
f=3	4.77	4.65	4.23	4.13					
f=4	4.63	4.54	3.95	3.90					
f=5	4.41	4.33	3.70	3.66					

Also, net interest is lower because the existence of the neutral state reduces the period of time in which a sell exposure would imply keeping the money at the cash rate. Overall, the highest average total return of 4.71 corresponds to the (Ω=2, d=0) case supporting again our previous conclusions.

4. Conclusions

Using a sample of returns characterizing the Bucharest Stock Exchange evolution we found that the profitability of the dual moving average crossover rule is significantly influenced by the way in which the rule is implemented. Some methodological combinations of parameters are more prone to generate superior performances biasing the conclusion towards recognizing technical analysis tools as potential generators of positive abnormal returns. Not only that, but as it was suggested in (Todea and Zoicas-Ienciu, 2011) in the case of the Romanian currency market, the profitability of technical analysis based trading rules tens to be time varying due to the manifestation of various linear and nonlinear dependencies in the price evolution. Thus, there are at least two major causes for the diversity of empirical results and conclusions found in the literature.

Appendix

Fig. 7 The average buy returns condition by the type of the investment space Ω when using a null

References

Brock W., Lakonishok J., LeBaron B. (1992) Simple Technical Trading Rules and the Stochastic Properties of Stock Returns, The Journal of Finance, Volume 47, pp. 1731–1764.

De Long J. B., Shleifer A., Summers L.H, Waldmann R.J. (1990) Noise Trader Risk in Financial Markets, Journal of Political Economy, University of Chicago Press, Volume 98(4), pp. 703-38.

Jensen M. C. (1978) Some Anomalous Evidence Regarding Market Efficiency, Journal of Financial Economics, Volume 6, Issue 2/3, pp. 95-101

Mitra L., Mitra G. (2011) The Handbook of News Analytics in Finance, John Wiley & Sons.

Park C.H., Irwin S.H. (2007) What do we know about the profitability of technical analysis? , Journal of Economic Surveys, Volume 21, pp. 786–826.

Todea A., Zoicas-Ienciu A. (2011) Technical Analysis and Stochastic Properties of Exchange Rate Movements: Empirical Evidence from the Romanian Currency Market, Romanian Journal of Economic Forecasting, Volume 14 (1), pp. 175-192.

White H. (2000) A Reality Check for Data Snooping, Econometrica, 68: 1097–1126