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Investment Strategy Optimization Using Technical Analysis and Predictive Modeling in Emerging Markets

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Abstract

This research examines the efficacy of technical analysis and predictive modeling in defining the optimal strategy for investing in the stocks indices of emerging markets. Trading strategies are set regarding different technical indicators based on moving averages and volatility of the value and returns on stock indices. Simple trading rules are generated using two moving averages – a long period and a short period moving average, and Moving Average Convergence-Divergence (MACD) and Relative Strength Index (RSI). Selected technical indicators are used as features in defining predictive model based on Least Squares Support Vector Machines (LS-SVMs). A LS-SVM classifier has been used in order to predict trend of the stock indices' value whereby the obtained outputs of the LS-SVM model are binary signals that can be used for defining the trading strategy. Comparing the results obtained from traditional statistical methods for predicting the trend of financial series and proposed LS-SVM model, it can be concluded that machine learning techniques capture the non-linear models which are dominant in the financial markets in more adequate way. Outperforming the results of Buy & Hold strategy and technical trading strategies, application of LS-SVM in decision making process on investing on the financial market significantly can contribute to maximization of profitability on investment.

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Keywords: Technical Analysis; Emerging Markets; Trading Strategy; Predictive Modeling; LS - SVM

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1. Introduction

The profitability of investing in financial asset depends on the possibility and success of predicting the future movement of the market prices of financial asset. Thus, the constant interest of investors in this particular field comes as no surprise. On the other hand, this issue represents a challenge for science both in terms of the choice of methodology as well as in terms of the theoretical basis of its application. If we were to assume that the financial markets are effective, we would not be able to create a model which would beat the market and provide excess returns to investors. Instead, a weak form of the Efficiency Market Hypothesis (EMH) assumes that all past prices of a stock are reflected in today's stock price, so that any attempt at modelling the future would imply the negation of the most important hypothesis on which the functioning of the financial market is based on in science. In reality, however, investors realize a certain amount of return by applying various methods of prediction, usually technical analyses, which are applied in a variety of asset markets.

Technical analysis is a kind of state-of-the-art method for predicting trends of asset prices. This analysis is based on the idea that prices move in patterns that can be detected and recognized by investors, and that the durations of these patterns are long enough to compensate for any transactional costs and losses that could be incurred due to false signals. The profitability of the trading strategy and investment strategy which is based on technical analysis has proven in several studies in the case of developed markets. Recently, the focus of technical analysis has shifted toward emerging markets, since they are now being recognized as important alternative source of investment opportunities. Nevertheless, the use of technical indicators has constantly been expanding. Technical analysis, in combination with fundamental analysis, increases the power of prediction models. Moreover, by implementing machine learning techniques such as support vector machines, genetic algorithms, artificial neural networks, fuzzy logic and chaos theory in financial market analysis, technical analysis can be used for the purpose of providing the necessary input for more advanced predictive models.

The aim of this paper is twofold. The first topic of study is the profitability of the technical trading rules implemented on a specific group of emerging markets – so called frontier markets - of the Southeast European countries. Starting with the assumption that the movement of stock prices is non-linear, but still implying some kind of trend, trading strategies can be defined based on moving averages and MACD and RSI indicators. Then, the technical indicators which are used to form the most profitable strategies are used as input vectors for the prediction model based on Least Square Support Vector Machine (LS-SVM), which is then evaluated. The results of this research show that in the capital market of Serbia, Croatia, Romania and Bulgaria, we can form a profitable trading strategy by using technical indicators, but that the predictive power of modelling significantly increases though the use of proposed machine learning technique. These analyses complete the insufficiently studied area of trading strategies on the capital markets in the region, and make their contribution in the form of a prediction model, whose use in defining the trading strategies can be considered effective.

The paper is structured as follows: the second section gives an overview of the existing literature on the topic of technical analysis and prediction models based on LS-SVM. How the trading strategies are defined is analyzed in this paper, including the formation of the prediction model, is explained in the third section of the paper. The fourth section of the paper outlines the empirical results and comparison of the effectiveness of the studied trading strategies, while the conclusions and future directions of research which are in accordance with them are presented in the final section.

2. Literature review

The role of the technical analysis and the trading strategies based on it in the optimization of the investment decisions has been studied to a great extent in academic and professional circles. Despite the fact that the participants in the financial markets actively use technical analysis in the formulation of trading strategies (Menkhoff, 1998; Cheung & Chinn, 1999; Gehrig &Menkhoff, 2006), the existing literature on this topic is quite controversial. On the one hand, the initial assumptions of technical analysis are at odds with the widely accepted Efficiency Market Hypothesis (Fama, 1970). It is clear that technical analysis has had its ups and downs over the past few decades, depending on the extent of the prevalence of this theory in academic circles. On the other hand, certain studies have shown that the technical trading strategies have not always provided an acceptable level of profitability, which resulted in additional skepticism in terms of their application (Fama&Blume, 1966; Van Horne & Parker, 1968; Jensen &Benington, 1970).

A detailed analysis of the studies on the performances of technical trading strategies is represented in the work done by Park and Irwin (2007). This analysis included a total of 137 studies which were carried out on the stock markets, foreign exchange markets and future markets during the period between 1960 and 2004. All of the studied material was divided into two groups: early studies (1960-1987) and modern studies (1988-2004). Although early studies analyzed application of only several simple trading rules and in most of the studies trading strategies were not tested in appropriate way, this group of studies was of grate significance for further development of technical analysis, because results disprove the efficacy of technical trading strategies. Modern studies mostly solved questions related to the testing of trading strategies and in the most cases (about 60%) confirmed the profitability of trade strategies based on technical analysis. The rest of the modern studies reported mixed results (about 20%) and negated the usefulness of technical analysis (about 20%).

Recent studies, however, neither favor nor diminish the unconditional application of trading strategies based on technical analysis. Quite the contrary, it is considered that success of technical trading rules cannot be generalized, and instead is temporary – in accordance with the Adaptive Market Hypothesis (Todea, Ulici&Silaghi,2009;Todea, Zoicas-Ienciu&Filip,2009). This theory that can be characterized as link between EMH and behavioral finance assumes that dynamic nature of the financial market, the real possibility for arbitrage and the investors' preferences implies non-stable relationship between risk and returns. Therefore, it can be noted that investment strategies "wax and wane, performing well in certain environments and performing poorly in other environments" (Lo, 2004). As a result, opposing attitudes in the studies on the performances of technical analyses can be considered relative, depending on the time and the market which is being studied. In an exhaustive study, Taylor (2014) reached the conclusion that success in technical trading rules depends on the conditions on the financial market, primarily (non)liquidity, and to a lesser extent macroeconomic (in)stability, including the ability to short-sell stocks, while Neely, Rapach, Tu, and Zhou (2010) connect trading strategy performance oscillations with business cycles.

An area which is gaining in significance in the field of prediction of yield on the financial market are new concepts such as support vector machines, genetic algorithms, artificial neural networks, fuzzy logic and chaos theory. In many studies, the algorithms of machine learning have proven to be quite effective in the prediction of the direction of movement of stock index values and thus contributed to the increase in the gain and decrease in the risk involved in trading. The frequently adopted methods include Artificial Neural Networks (ANNs) (Boyacioglu, Kara&Baykan, 2009), linear and multi-linear regression (LR, MLR) (Atsalakis&Valavanis, 2009), genetic algorithm (GA) (Atsalakis&Valavanis, 2009), and Support Vector Machine (SVM) (Huang, Nakamori& Wang, 2005). According to Wang and Choi (2013), the methods most widely used for predicting the stock market trend are the approaches based on Support Vector Machine (SVM). In Phichhang and Wang's (2009) study, it was further indicated that in most cases the Least Squares Support Vector Machines (LS-SVMs), and SVMs outperform other machine learning methods, since in theory they do not require any previous a priori assumptions regarding data properties. Moreover, they guarantee an efficient global optimal solution.

Studies in EU markets show that predictive power of technical analysis is greater in small and medium sized capitalization markets (Metghalchi, Marcucci& Chang, 2012), but also in the world's emerging markets (Fifield, Power & Donald Sinclair, 2005; McKenzie, 2007;Heyman, Inghelbrecht&Pauwels, 2011). Nevertheless, there is a lack of significant empirical evidence in literature on profitability of investment strategies in European frontier markets. Research studies of investment opportunities in stock markets that will be analyzed in this study are mainly theoretical (Bradić-Martinović,2006;Arnerić, Jurun&Pivac, 2007;Vuković, Grubišić&Jovanović, 2012). Profitability of trading strategies based on MACD and RVI indicators is proven as same as the need for their optimization in order to be used efficiently in emerging markets (Erić, Andjelić&Redzepagić,2009). On the other hand, trading strategies based on moving averages crossover rules could lower investment risk (Anghel, 2013). Studies in the region also showed that trading strategies based on artificial neural networks, fuzzy logic and neuro-fuzzy systems over performed technical trading rules (Anghelache&Trifan, 2013), but we found no evidence on performance of SVM models in studied capital markets, especially LS-SVM.

3. Methodology and data

3.1. Data description

Trading rules and prediction models are applied on the stock indices of capital markets that are categorized as a subset of less developed emerging markets according to Standard and Poor's (S&P) and MSCI (Morgan Stanley Capital International) categorization. Regarding indicators that include measures of size (market capitalization and the number of listed domestic companies) and liquidity (the value of traded shares), selected stock markets of Serbia, Croatia, Romania and Bulgaria are classified as frontier markets[1]. As it can be noticed from Table 1, the market capitalization of selected frontier markets is very small. If it is compared to market capitalization of some emerging markets in the Balkans and Eastern Europe (for example: Hungary, Poland, Turkey and Czech Republic) expressed in US dollars, the market capitalization of the Serbian stock exchange is 2.83 to 41.44 times smaller (see http://wdi.worldbank.org/table/5.4). The gap is even bigger if we consider market liquidity (6.5 to 55.25 times smaller) and turnover ratio (7.57 to 36.89 times smaller) of the Serbian stock market compared to the aforementioned emerging markets. However, relevant indices of these stock markets are rated as blue-chip indices and included in the MSCI Frontier Emerging Market Index and S&P frontier indices. Thus, it can be concluded that these markets can be a sound investment mostly because they provide significant diversification benefits for international investors due to the low correlation between the frontier and developed markets (Spiedel&Krohne, 2007; Jayasuriya&Shambora, 2009; Berger, Pukthuanthong& Jimmy Yang, 2011).

Table 1.Stock market development indicators for 2012.

Country	Stock exchange	Market capitalization		Market liquidity*	Turnover ratio**	Number of listed domestic companies	S&P/Global Equity Indices***
		$ millions	% of GDP				
Bulgaria	Bulgarian Stock Exchange – Sofia	6,666	13.1	0.7	4.9	387	-8.1
Serbia	Belgrade Stock Exchange	7,451	19.9	0.8	3.7	1,086	-
Romania	Bucharest Stock Exchange	15,925	9.4	1.3	11.5	77	9.8
Croatia	Zagreb Stock Exchange	21,560	36.4	0.8	2.3	184	-5.2

*Value of shares traded presented as a percentage of GDP

**Value of shares traded presented as a percentage of market capitalization

***S&P Global Equity Indices measure the U.S. dollar price change in the stock markets covered by the S&P/IFCI and S&P/Frontier BMI country indices

Source: The World Bank (available at http://wdi.worldbank.org/table/5.4, retrieved on April 9, 2014)

In this study we use the daily closing values of selected stock exchange indices that represent the most liquid stocks on the market: for the Belgrade Stock Exchange – Belex15, the Zagreb Stock Exchange – Crobex10, the Bucharest Stock Exchange – BET, and the Bulgarian Stock Exchange – SOFIX. The data period is approximately 5 years long depending on data availability – from 2009 until October 1, 2013. The data sets were obtained from the official web sites of the stock exchanges and are expressed in national currencies.

In order to investigate the consistency and profitability of the proposed trading strategies, the data sets were divided into two sub-samples. The first sub-sample period starts at the beginning of 2009 and lasts until the end of 2012. It is considered an in-sample period. The second sub-sample period starts from the beginning of 2013 and lasts until the October 1, 2013. It is considered an out-of-sample period. Regarding technical trading strategies, on the in-sample data we test consistency of trading rules, while in the case of LS-SVM the same data set is used for learning the prediction model. The second period is used for validation of both proposed type of trading strategies.

[1]Available at http://www.msci.com/products/indexes/market_classification.html, retrieved on April 9, 2014.

3.2. Methodology

The technical analysis uses numerous qualitative and quantitative methods to analyze the asset price trends. The simplest qualitative methods are based on the charting of asset prices and trading volume in order to identify patterns that can be used to achieve profits. Technical indicators are quantitative methods and represent rather simple mathematical expression of price and volume changes. Investors use a combination of both methods in order to provide a more precise overview of market trends.

In this study we will use the most common technical indicators – moving averages (MA), moving average convergence-divergence (MACD) and the relative strength index (RSI). Technical trading rules are based on the dual moving averages crossover (DMAC) and trading signals generated from MACD and RSI indicators. The best performing indicators will be used as inputs for construction of LS-SVM prediction model.

3.2.1. Technical trading strategies

A technical trading strategy is composed of a set of trading rules that are used to generate trading signals. In general, commonly used trading systems rely on one or two technical indicators that define the timing of trading signals. By changing the combinations of technical indicators, numerous trading rules can be set. The most popular ones among investors are the moving average based trading systems.

The Moving Average (MA) represents the average of the price of the financial asset over a certain period of time. This is a frequently used indicator, whose aim was to smooth the trend of asset prices. Considering the fact that the trend of market prices is extremely volatile, it is not practical to apply trading rules based on this indicator, since this could lead to the generation of too many signals, including false ones. That is why in defining the trading rules some form of MA – simple MA, weighted MA and exponential MA are most frequently used. In this study, the exponential MA (EMA) was used, which in the calculation of the average price for a certain period of time t assigns greater significance to prices in shorter time intervals. It can be calculated using the following formula:

$$\mathrm{EMA_t} = \mathrm{P_t} * \mathrm{k} + \mathrm{EMA_{t-1}} * (1-\mathrm{k}), \mathrm{k} = 2/(\mathrm{N}+1) \tag{1}$$

where the following symbols have the following meaning: P_t - asset price in the period t, k - smoothing factor, N – the number of periods within the EMA is calculated.

The trading strategies based on the MA buy and sell signals generate in the cross-section of stock prices and MA, or in the cross-section of two or more MAs. In this paper, DMAC trading system based on the cross-section of two EMAs were used. This type of trading system involves only two EMAs calculated for different time periods. If the EMA is calculated for 20 days or less, it is regarded as a short-term EMA. If it is between 20 and 50 days, it is a medium-term EMA, and if it exceeds 50 days, it is a long-term EMA (Cheung, Lam& Yeung, 2011). In the case of this type of trading strategy, buy and sell signals at the end of period *t* are generated by comparing two EMAs in the following way:

$$S_t = \begin{cases} 1 \text{ if } \mathrm{EMA_{s,t}} \geq EMA_{m,t} \text{ or } \mathrm{EMA_{s,t}} \geq \mathrm{EMA_{l,t}} \\ -1 \text{ if } \mathrm{EMA_{s,t}} \leq EMA_{m,t} \text{ or } \mathrm{EMA_{s,t}} \leq \mathrm{EMA_{l,t}} \end{cases} \tag{2}$$

According to this rule, buy signal in time *t* ($S_t = 1$) is obtained when short-term EMAs ($EMA_{s,t}$) cross the medium ($EMA_{m,t}$) or long-term EMA ($EMA_{l,t}$) from below. This kind of situation indicates a growth in the price and an upward trend, when the best response is to be trading on the market. The sell signal in time *t* ($S_t= -1$) is obtained in the reverse situation – when the short-term EMA ($EMA_{s,t}$) crosses the medium ($EMA_{m,t}$) or long-term EMA ($EMA_{l,t}$) from above. In this kind of situation the investors withdraw from the market, since this kind of signal indicates a downward trend of asset prices. Since we are using Variable Length Moving Average rules without a band, every trading day in the data set is classified either as a buy or sell day.

The Moving Average Convergence-Divergence (MACD) represents a widely used indicator for recognition and monitoring of the trend, but also changes in the trend. In terms of calculation this indicator in point *t* can be expressed as the difference between short-term EMAs and medium or long-term EMAs of the asset closing price, that is:

$$MACD_t = EMA_{s,t} - EMA_{(m,l),t} \tag{3}$$

The most frequently used combination of the EMA is the 12-period and 26-period EMA for short and longer term EMA, respectively. However, we can also use other combinations depending on the conditions on the financial market and the aims of the investors (Appel, 2005; Erić et al., 2009).

Upward and downward trend movements can be recognized based on the values of the MACD: in the case of an upward trend, the value of this indicator will be positive, while the negative value of the MACD signalizes a downward trend. The buy signals and sell signals are defined based on the crossover system, where the signal line is represented by a 9-period EMA of MACD in the following way:

$$S_t = \begin{cases} 1 \text{ if } \mathrm{MACD_t} \geq EMA_{9,t} \\ -1 \text{ if } \mathrm{MACD_t} \leq \mathrm{EMA_{9,t}} \end{cases} \tag{4}$$

The signal to buy in moment *t* ($S_t = 1$) is generated if the value of the $MACD_t$ is greater than the value of the9-periodMACD$_t$($EMA_{9,t}$), while the signal to sell stocks (S_t= -1) is the decrease in the value of theMACD$_t$ to a level below $EMA_{9,t}$.

The Relative Strength Index (RSI) is a technical indicator which measures the range of the oscillations of the prices of the financial asset. The value of this oscillator is obtained using the following formula:

$$RSI_t = 100 - \frac{100}{1+RS_t} \; where \; RS_t = \frac{\sum_{n=t}^{t-d} \max(0, P_n - P_{n-1})}{\sum_{n=t}^{t-d} \left|\min(0, P_n - P_{n-1})\right|} \tag{5}$$

The value of this ratio ranges from 0 and 100. If the value is closer to the upper level, it could be concluded that the increase in price is greater and more frequent in relation to their decrease, which also suggests that a specific financial asset should be sold, since in such a situation we expect the prices to go down to the average level, that is, we expect a trend reversal. If, however, the value of the ratio approaches the lower value, it is a signal of the decrease in the value of the financial instrument which is more frequent, but following the logic of the trend reversal, the specific financial instrument should be bought, since the losses will be neutralized due to changes in the trend in the near future.

The trading signals can be generated in different ways, depending on the set limits (Wong, Manzur& Chew, 2010). In this study, the upper and lower limits are set at the levels of 70 and 30, respectively. The signal to buy is generated at the moment when the value of the RSI crosses the lower limit of 30 below, while the signal to sell is generated when the value of the RSI exceeds the lower level of 70 above.

3.2.2. Trading strategies based on LS-SVM prediction model

The remainder of the paper gives a brief overview of the Least Square Support Vector Machine LS-SVM method, one of the modifications of the support vector methods. These methods belong to the class of Supervised Machine Learning techniques whose prominent characteristic is learning based on known examples. A supervised machine learning algorithm uses the training set to generate an output function that maps instances in *x* to labels in *y*.

The SVM performs a non-linear mapping of the data into a multidimensional space, and then uses linear functions to form the boundaries for decision-making processes in the new space. Non-linear problems in the original space transform into linear problems in multidimensional space. One of the features of an SVM was suggested by Vapnik, and that was that the problems of nonlinear classification and regression can be solved using methods of convex quadratic programming (QP). The Least Squares Support Vector Machines, proposed by Suykens and Vandewalle (1999) include a set of linear equations which are solved instead of QP for classical SVMs. Therefore, LS-SVMs are more time-efficient than standard SVMs, but with lack of sparseness. A LS-SVM has excellent generalization capabilities, in the sense that its output hypothesis should accurately predict the labels of previously unseen examples.

In this study, we use an LS-SVM prediction model to form a trading strategy on the selected frontier markets.

3.2.2.1. The basics of LS-SVM theory

Let's study a training group of a total of *N* examples $T = \{x_i, y_i\}_{i=1}^{N}$. In the learning phase, the model is formed based on familiar training data $(x_1, y_1), (x_2, y_2), \ldots, (x_N, y_N)$, where x_i are the input vectors, and y_i are the labels of binary classes that were assigned to them. Each input vector consists of numeric features, while$y_i \in \{-1,+1\}$. In the application phase, the trained model, based on the new inputs $x_1, x_2, \ldots, x_N$, makes predictions of the output values $y_1, y_2, \ldots, y_N$.

After solving the optimization problem defined in (Suykens&Vandewalle, 1999), the function of the separation of LS-SVM classifications is defined as:

$$y(x) = sign\left[\sum_{k=1}^{N} \alpha_k y_k K(x, x_k) + b\right] \tag{6}$$

where$\alpha_k$represents the support vectors (Lagrange multipliers), and *b* is a constant.$K(x,x_k)$ represents the Kernel Function. This is a function defined by the dot product of *x* and x_k. The Kernel Function describes the behavior of the support vectors, enabling training data to be transformed into a higher dimension. In this dimension, the support vectors can then enable classification based on linear decision boundaries. The Gaussian kernel or RBF (Radial Basis Function) was used in this study as a result of its tendency to perform well under general smoothing assumptions. The kernel is defined as:

$$K(x, x_k) = e \frac{-\|x - x_k\|^2}{\sigma^2} \tag{7}$$

A grid-search technique, in combination with a k-fold cross validation, was used to determine the parameters (C, σ^2). This process is described in more detail in (Wang & Choi, 2013).

3.2.2.2. Model formulation

The selection of input features is crucial for defining an accurate prediction model but there is no general rule that can be followed. Since the goal of this study is to predict the stock market trend, the technical indicators were used as prediction features. In order to provide as simple method which can be applied in general, only data which was easy to access in all stock markets was used in the study. Thus, the method proposed in this article adds a practical component to stock prediction

The variables to be predicted are the future trends of the stock market. The attribute which serves as a label for the class is a categorical variable used to indicate the movement direction of the index over time *t*. If the logarithmic return over time *t* is larger than zero, the indicator is 1. Otherwise, the indicator is −1.

This study represents a further development of our prior work (Marković, Stanković,Stojanović&Božić, 2014), with new results and a more in-depth analysis. These new results primarily refer to the use of a proposed prediction model, originally created based on the characteristics of the Belex15 index for the stock market trend prediction of indices from other frontier markets. The obtained results indicate good predictive abilities and stable characteristics of proposed prediction model, as well its good possibility for generalization. Based on previous studies and analyses, the proposed LS-SVM model is defined in the following way:

$$y_t = LS - SVM(r_{t-1}, EMA_{10t-1}, MACD_{t-1}) \tag{8}$$

where r_{t-1} represents the value of the logarithmic return of the previous day of trading, EMA_{10t-1} 10-period EMA of the previous day of trading and $MACD_{t-1}$ represents the value of MACD (12,26) indicator of the previous trading day. In order to form the model, we used the library LS-SVMlab (De Brabanter et al., 2011).

Based on the obtained trend prediction, we can define the trading signals in the following way:

$$S_t = \begin{cases} 1 \; if \; S_{t+1} \geq S_t \\ -1 \; if \; S_{t+1} \leq S_t \end{cases} \tag{9}$$

where the buy signal (S_t= 1) is generated if an increase in the trend is noted the next day in comparison to today, and the sell signal (S_t= -1) if the prediction indicates that the trend will decrease the following day.

4. Results and discussion

In this study we analyzed a selection of trading strategies frequently used in the world capital markets today. The following DMAC trading systems were tested: EMA (1,50), EMA (1,150) and EMA (1,20), although the last one is not very common since it is based on the crossover of two short-term EMA. However, due to the high autocorrelation and volatility, we assumed that short-term prediction may give better results than long-term. Trading strategies based on MACD and RSI indicators were also tested. The obtained results were compared to the returns on the benchmark – the Buy & Hold strategy. Returns on investments in the case of a specific stock market index were calculated as the differences between daily index values presented in national currencies, multiplied by the generated trading signal for the studied day. Gross returns were defined as the cumulative capital gains for a specified period of time, excluding transactional costs, while when calculating net returns, the provisional transactional costs of 1% of the transaction value were included.

All the technical trading strategies were applied on the in-sample data, which were divided in 4 sub-periods. These sub-period tests have multiple purposes. The analysis of the results in different periods of time should show the consistency of trading rules. As it can be noticed in Table 2, not all trading strategies show the same efficiency in the studied period. In the case of Belex15, the best performing strategies are the ones based on EMA, especially EMA (1,20) and MACD. In almost all the cases, these strategies beat the market, since they provide a higher net return compared to the Buy & Hold strategy. However, in the case of Crobex10, the strategies show no significant consistency. Trading strategies based on short-term EMAs outperformed benchmarks in three out of four sub-periods. Due to the high transaction cost, the obtained net returns are negative. The only strategy that can under certain conditions gain profit is EMA (1,50). However, in the case of market turbulence, the proposed trading strategy cannot beat the market. In the case of SOFIX and BET, the best performing strategies are EMA (1,20), EMA (1,50) and MACD. Nevertheless, losses due to transaction costs are very high, and only in several cases did the proposed strategies obtain significantly higher net returns compared to the benchmark. However, in none of the cases did the trading strategies based on RSI perform well. This is due to the fact that the RSI trading strategies are profitable only in non-trending environments (Wong et al., 2010). Thus, it can be concluded that on the proposed markets, sophisticated trading-following strategies can be profitable. Since this indicator is not suitable for setting trading rules in this analysis, it will not be tested in the out-of-sample data set.

Table 2. Cumulative returns generated by trading strategies on the in-sample data set.

Index	Currency	Trading Strategy	2009		2010		2011		2012	
			Gross	Net	Gross	Net	Gross	Net	Gross	Net
Belex15	RSD	EMA (1,20)	448.65	361.66	156.07	52.61	302.18	175.42	234.14	177.37
		EMA (1,50)	461.09	422.33	8.81	-58.49	385.82	343.64	186.18	144.99
		EMA (1,150)	-73.15	-85.97	-32.13	-105.8	295.60	288.08	40.00	5.18
		MACD	621.78	559.77	203.99	106.64	-116.08	-254.05	177.28	116.24
		RSI	13.60	-124.14	1.41	-143.5	27.82	-146.13	-14	-170.81
		Buy & Hold	130.24*		-26.91*		-158.00*		33.72*	
Crobex10	HRK	EMA (1,20)	62.24	-3.97	239.74	-245.2	51.14	-236.9	-131.87	-500.7
		EMA (1,50)	-379.4	-446.6	308.18	155.71	164.7	53.55	-105.17	-394.12
		EMA (1,150)	-41.86	-41.86	-46.68	-103.1	231.72	219.86	-31.57	-60.33
		MACD	-204.9	-282.5	184.12	-18.51	153.82	-35.76	74.47	-110.91
		RSI	-29.81	-163.75	-5.36	-177.8	0.28	-244.05	4.25	-130.07
		Buy & Hold	68.63*		95.14*		-187.62*		11.23*	
SOFIX	BGN	EMA (1,20)	51.38	3.24	55.33	-11.77	144.77	21.26	-28.83	-173.75
		EMA (1,50)	-67.42	-105.92	35.53	-16.64	172.41	137.64	50.95	-8.13
		EMA (1,150)	-230.8	-243.69	44.79	-24.57	82.35	49.61	34.59	31.45
		MACD	94.42	63.35	87.75	29.20	150.97	105.07	-42.21	-111.93
		RSI	11.59	-46.12	-19.05	-92.92	-11.46	-135.74	4.18	-20.85
		Buy & Hold	155.28*		-64.29*		-44.63*		25.69*	
BET	RON	EMA (1,20)	1303.46	238.28	880.58	-705.2	803.73	-849.38	729.34	-597.12
		EMA (1,50)	2519.1	2221.14	1162.58	-225.2	1239.87	863.49	1134.2	140.76
		EMA (1,150)	-338.4	-379.48	-573.18	-1495	1064.01	675.48	-235.72	-857.15
		MACD	-969.59	-1752.6	1075.62	205.0	892.79	-318.33	1067.9	187.30
		RSI	337.79	-497.14	-116.91	-668.8	74.94	-418.57	-137.13	-424.14
		Buy & Hold	1767.29*		615.30*		-1023.41*		985.36*	

*Returns are not adjusted for transaction costs

Source: Authors' calculation

The selected technical trading strategies and strategies based on the LS-SVM prediction model were both tested in the out-of-sample period. The results of the tested trading strategies are presented in Table 3.

All of the proposed technical indicators in the case of Belex15 contribute to the investment strategy optimization. However, the prediction power of the LS-SVM model outperformed the results obtained by the technical analysis, and despite more frequent trading, enabled investors to gain profits that were 43.23% higher compared to the best performing technical trading strategy.

In the case of Crobex10, the LS-SVM trading strategy was the only profitable alternative for investors in the studied period of 2013. This trading strategy generated a net return which is 24.13% higher than the one generated by the Buy & Hold strategy. The technical trading strategies could not capture the patterns of index value movements adequately and obviously generated false trading signals, because all strategies in this period recorded losses.

In the case of investment in SOFIX and BET market indices in the studied period, none of the trend-following strategies could beat the market. However, the LS-SVM trading strategies provide the highest gross returns: for SOFIX 180.72% and for BET 72.46% higher than market returns, after the subtraction of provisional transaction costs, the cumulative net returns were unlikely to be optimal for small and active investors.

Nevertheless, it is important to note that transactional costs in this study are provisional and that could vary depending on the stock exchange and the size of the order. On the more developed stock exchanges these costs are usually lower and could be additionally decreased in the case of large investors.

Table 3. Cumulative returns generated by trading strategies on the out-of-sample data set.

Index	Currency	Trading Strategy	Number of trading days		Return on investment		Number of trades
			Buy	Sell	Gross	Net	
Belex15	RSD	EMA (1,20)	121	66	113.61	50.31	11
		EMA (1,50)	108	76	115.75	62.22	9
		EMA (1,150)	98	89	28.13	17.57	1
		MACD	87	100	108.65	22.13	15
		LS-SVM	103	84	256.29	139.31	23
		Buy & Hold	187		0.59*		-
Crobex10	HRK	EMA (1,20)	70	118	125.74	-125.1	23
		EMA (1,50)	97	91	27.74	-184.0	19
		EMA (1,150)	114	74	81.88	-54.1	12
		MACD	67	121	51.08	-44.74	8
		LS-SVM	76	112	448.7	153.76	29
		Buy & Hold	188		37.10*		-
SOFIX	BGN	EMA (1,20)	147	40	83.43	-7.11	44
		EMA (1,50)	181	6	83.11	59.09	6
		EMA (1,150)	187	0	111.37	111.37	0
		MACD	108	79	62.63	28.91	8
		LS-SVM	124	63	201.27	78.97	31
		Buy & Hold	187		111.37*		-
BET	RON	EMA (1,20)	120	70	772.39	-448.7	22
		EMA (1,50)	132	58	718.33	65.72	12
		EMA (1,150)	173	17	622.55	89.37	10
		MACD	83	107	785.03	337.26	8
		LS-SVM	115	75	951.34	614.98	8
		Buy & Hold	190		689.35*		-

*Returns are not adjusted for transaction costs

Source: Authors' calculation

5. Conclusion

The aim of this study was to test the prediction power and usefulness of technical analysis as a widely implemented model for the recognition and monitoring of trend movements in financial markets, and as an input for the LS-SVM trend prediction model. Analyses were conducted on the small emerging markets of Southeast Europe. The most commonly used technical indicators were implemented in the process of investment strategy optimization and tested in different periods of time in order to prove consistency. The results showed that a significant consistency of specific trading indicators could barely be obtained in the studied period. However, in most cases, technical analysis proves to have a certain level of prediction power that could gain excess returns.

As an input for the LS-SVM prediction model, EMA and MACD prove to be acceptable indicators of trend movements. Trading strategies based on the LS-SVM model outperformed all technical trading strategies and the benchmark strategy. Although the net returns under the assumption of fixed transactional costs of 1% of the executed order value in some cases were unlikely to be optimal for small and active investors, the obtained results were encouraging. Future work should focus on the selection of additional input variables for the prediction model in the class of technical and fundamental indicators. Precision in modeling stock market movements could be obtained by adjusting the model parameters by means of a more sensitive and comprehensive parameter setting.

Additional improvements of the proposed prediction model for the purpose of the optimization of investment strategies on the financial markets could be made by altering mechanism for generating trade signals. Volatility bands could decrease the number of false signals, adjust the frequency of trading according to the conditions on the markets and contribute to gaining excess profits.

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