

SMOOTHING TECHNIQUES FOR MARKET FLUCTUATION SIGNALS

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Abstract. The financial crisis of 2008–2009 caused lots of discussions between Academia and as a result researches on financial crisis and bubble prediction possibilities appeared. Academia shows its growing interest in the issue during the last decade. The majority of researches made are based on different forms of forecast used. Some of previous studies claim that the trend of the stock market can be forecasted using moving average method. After the finance market crashed, a need to forecast further possible bubbles arises. As the economics of the Baltic States is very sensitive to such bubbles it is very important to forecast preliminary the trends of the finance markets ant to plan the right actions in order to temper such bubble influence on the national economics. Although economic theory is opposite to the technical analysis theory which is the main tool for traders in stock markets it is used widely. This paper examines whether a proper technical analysis rule such as Exponential Moving Average (EMA) has a predictive power on stock markets in the Baltic States. The method is applied to OMX Baltic Benchmark Index and industrial indexes as they are more or less sensitive to the main index fluctuations. The results were compared using systematic error (mean square error, the mean absolute deviation, mean forecast error, the mean absolute percentage error) and tracking signal evaluation, CAPM method and appropriate period of EMA finding for each market fluctuations. The conclusions made during the research suggest new research issues and new hypotheses for its further testing.

Keywords: technical analysis, Exponential Moving Average, bias, forecast, stock, market trend, CAPM, fluctuation signal.

IŠLYGINIMO METODŲ TAIKYMAS RINKOS SVYRAVIMAMS PROGNOZUOTI

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Santrauka. 2008–2009 m. finansų krizė sukėlė daug diskusijų tarp mokslininkų. Buvo tiriama, ar įmanoma prognozuoti finansų krizes ir rinkų burbulus. Pastaruosius dešimtmečius mokslininkai vis labiau domisi šia tema. Dauguma atliktų tyrimų grindžiami įvairiais prognozavimo tipais. Remiantis kai kuriais ankstesniais tyrimais, akcijų rinkos tendencijas galima prognozuoti taikant slankiojo vidurkio metodą. Žlugus finansų rinkoms, atsirado poreikis ateityje numatyti besiformuosiančius rinkų burbulus. Kadangi Baltijos valstybių ekonomika yra labai jautri tokiems rinkų burbulams, labai svarbu prognozuoti ateities vystymosi finansų rinkų tendencijas ir tinkamai planuoti veiksmus, siekiant sušvelninti tokių burbulų įtaką nacionalinei ekonomikai. Nors ekonominė teorija yra priešinga techninės analizės teorijai, kuri yra pagrindinė prekybininkų priemonė akcijų rinkose,

ji yra plačiai taikoma. Šiame straipsnyje nagrinėjama, ar tinkamai pritaikyta techninės analizės taisyklė, pvz., eksponentinis slankusis vidurkis (ESV) turi prognozavimo galios vertybinių popierių rinkose Baltijos šalyse. Metodas taikomas OMX *Baltic Benchmark* indekso ir ūkio šakų indeksų prognozei atlikti, nes šie indeksai yra daugiau ar mažiau jautrūs pagrindinio indekso svyravimui. Rezultatai buvo lyginami taikant sisteminės paklaidos įvertinimo metodus: vidutines kvadratines paklaidas, vidutines absoliučiąsias paklaidas, vidutines prognozavimo paklaidas, vidutines absoliučiąsias paklaidas ir sekimo signalo įvertinimą, CAPM metodą, siekiant ištirti tinkamą ESV laikotarpio kiekvienos rinkos prognozei atlikti. Grafinė analizė buvo naudojama siekiant nustatyti, ar ESV gali numatyti pagrindines vertybinių popierių rinkų svyravimų tendencijas. Tyrimo metu suformuluotos išvados sukuria prielaidas naujoms hipotezėms atsirasti ir tyrimams atlikti ateityje.

Reikšminiai žodžiai: techninė analizė, eksponentinis slankusis vidurkis, paklaida, prognozė, vertybiniai popieriai, rinkos tendencijos, CAPM metodas, svyravimas, signalas.

1. Introduction

Investment decision-making is often based on the following three dimensions: value, time and risk. The main characteristic of the stock market is its dynamic condition, so value and risk are the measures which can only be forecasted but not known exactly in advance. Financial crisis in the beginning of the 21st century was caused by crashes in stock markets. Nowadays economists analyze the current financial crisis and try to find the main reasons why the world economy constantly suffers from booms and busts (Dzikevicius, Zamzickas 2009). Račickas and Vasiliauskaitė (2010) identified one of the major financial crisis depth indicators. It is the country's stock market indexes. Stock market index observation allows determining current stock market situation. If Academia finds the appropriate way to forecast at least exact market trend or its fluctuation signals, the subsequence of such financial crisis as the world has seen in the 21st century can be more opportune for the further financial markets and national economic development. As the globalization processes are spread widely between different countries, the crash of one stock market causes the influence on other stock markets in other countries.

The events of the last two years indicated the principles of investors' behaviour: an inadequate risk assessment, the desire to obtain abnormal returns, the orientation of short-term investment horizons or the speculation. Such attitude skews stock market trends and its behavior. As the investment process is an important part of investment banks', insurance companies', etc. activity, it should involve more efficient and accurate forecasting methods. So the aim of this study is to find out more appropriate forecasting techniques suitable to indicate the fluctuations of the stock market. The previous study (Dzikevicius et al. 2010) was based on analysis of simple Technical Analysis (further TA) rules. The results implied that application of simple trading rules to forecast stock prices can generate significant forecasted value errors and deviations from real prices and it is not appropriate to generate price movement trends. The continuous research (Dzikevicius, Saranda 2010) was the first academia research of using TA to predict the values for OMX Baltic Benchmark Index and compare it with S&P 500 Index of US using an exponential smoothing method – the exponential moving average (further – the EMA). The results were affirmative: the exponential smoothing method was appropriate to indicate the future values of S&P 500 and OMX Baltic Benchmark indexes. With the reference to previous researches smoothing techniques will be tested again to decide whether it is a powerful tool to forecast stock market fluctuation signals. The OMX Baltic Benchmark PI Index and related sector indexes are the objects to be forecasted to find out the trend of the Baltic region stock markets.

2. The review of applied forecasting and risk evaluation methods

Investors' endeavor that the value of assets held steady improves. In addition they are interested in not just increase in the value but also the speed of value growth. Only initial asset price is known. Two dimensions such as final asset price and current profit are unknown (Rutkauskas, Martinkutė 2007). Technical factors are related to the securities market which focuses on the evolution of prices and trade circulation, demand and supply factors. An important statistical tool which allows identifying the market conditions is an equity index (Norvaišienė 2005). In our case OMX Baltic Benchmark PI index is a statistical stock market price dynamics measure tool. Securities market is still relatively new for individual investors. As the new type of investors such as an individual investor appeared in the stock market, a huge flow of information on the investment management and assessment issue is needed (Jurevicienė 2008). Growing stock market and rising activity of the investors attracts more growing attention (Dudzevičiūtė 2004).

TA researchers Edwards and Magee (1992), Myers (1989), Pring (1993) described this method as a technique which needs patterns of history prices of a financial instrument to be used. The Moving Average rule is one of the numerous methods with a common set of TA basic principles (Caginalp, Balenovich 2003). Klimavičienė and Jurevičienė (2007) quizzed investors to determine their investment preferences. The survey showed that 17.3% of the respondents invested into securities, 14.3% of respondents invest directly into shares, and 15.4% of the survey divestors tors speculated and invested. The survey made by Mizrach

and Weerts (2007) showed that 52% of semi-professional traders used simple moving rules and 56% preferred chart patterns. The survey made among market participants by Taylor and Allen (1992) showed that 90% of respondents placed some weight in TA.

Brock et al. (1992) found that TA has a support in forecasting U.S. Dow Jones index. Lo, Mamaysky and Wang (2000) reviewed the literature and summarized that technical analysis rules can be effective to extract useful information from market prices. Technical analysis tests made by Academia provide slightly different results. Parisi and Vasquez (2000) have tested variable moving average (VMA) rules and concluded that VMA usage is profitable in Chile. On the other hand, Ratner and Leal (1999) found that these rules do not work in the same market. Bessembinder and Chan (1995) found that VMA short-term rules are profitable in Japan while later in 1999 Ratner and Leal (1999) made opposite conclusions. Ito (1999) test results imply that VMA rules add some value in Indonesia meantime Ratner and Leal (1999) state that they do not. Barkoulas et al. (2000) tested the model of an autoregressive fractionally integrated moving average in the Greek stock market and concluded that price movements are influenced by realizations from the recent past and the remote past. Bokhari et al. (2005) tested some smaller companies on UK indexes FTSE 100, FTSE 250 and FTSE Small Cap and concluded that in these markets the higher predictive ability of technical trading rules exists.

Metghalchi et al. (2007) concluded that technical trading rules have power to predict and they can be used to design a trading strategy in the Austrian stock market. Lönnbark and Soultanaeva (2009) were interested in studying whether technical trading rules are profitable on the Baltic stock markets and evaluated different VMA rules on index data from Vilnius, Riga and Tallinn markets and found that VMA rules exhibit no profitability when testing method accounts for dependence structure in the data. As the analysis of the literature on TA was made, it can be concluded that most authors make researches of the methods setting a goal of getting a profit by forecasting stock markets but not to predict their fluctuations. They place a lot of attention to the stock returns but not stock or index trends. Marshall et al. (2008) tested whether the relationship between a firm's industry and the profitability of TA exists and they have not found any substantiation. Kannan et al. (2010) implied that most common averages are 20, 30, 50, 100, and 200 days.

This study will find out whether these common averages are predictive in the Baltic stock market. Girdzijauskas *et al.* (2009) have found out that the exponential growth models are more suitable for the modeling processes in the near future. Exponential smoothing method is a part of both the quantitative decision making methods and TA and it can be described as the forecast method when the estimates are used in the weighted average of the values of the time series (Pabedinskaitė 2007). Tillson (1998) advised to use specific smoothing Constant α :

$$\alpha = \frac{2}{n+1},\tag{1}$$

where n is EMA number of days. For the markets signal forecast exponential smoothing is used:

$$F_{t+1} = \alpha Y_t + (1 - \alpha) F_t, \qquad (2)$$

where α is smoothing Constant (0< α <1). In our case we modify (2) formula to calculate n day EMA:

$$F_{t+1} = \alpha Y_t + (1 - \alpha)F_t = F_t + \alpha (Y_t - F_t) = F_t + \frac{2}{n+1}(Y_t - F_t).$$
(3)

With the limitation $\lim_{n\to\infty} \frac{2}{n+1} = 0$. In this research we test particular case when $n \in (2;100)$.

The selected forecast method – the EMA – efficiency is based on the forecast's accuracy level (Pilinkienė 2008). Makridakis *et al.* (1983) advised to use the following forecast accuracy measures: Mean Error (ME), Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Standard Deviation of Errors (SDE), Mean Percent Error (MPE), Mean Absolute, Percent Error (MAPE), etc. In our study we use MSE, MAD, MFE, MAPE and Tracking signal measures to evaluate the accuracy of the forecast trend (Table 1).

Every forecasting process is related to risk and is relevant to all stock market participants. Aniūnas *et al.* (2009) emphasized that investors need to evaluate acceptable risk level during analysis of investment models and before making decisions. Different mathematical – statistical models are used to evaluate risk. Market risk evaluation needs to quantify the risk of losses and its volume due to movements in financial market variables (Jorion 2003). The investor can not precisely determine the real value of the investment. Higher risks mean the greater potential dispersion of the profitability. By 1960, the portfolio of management performance was measured mainly in accordance with the profitability achieved.

The concept of the risk has been known but investors did not know how to measure it quantitatively. Modern portfolio theory has shown investors how the risk can be quantified by the standard deviation of profitability. At the same time no quantitative measures related both profitability and risk. These factors were considered separately, i.e. investors are grouped into similar risk investment classes, according to the profitability of the standard deviation and then alternative investment return for only certain classes of risk is evaluated (Dzikevičius 2004). Smaller standard deviation means lower investment risk level and vice versa. Risk cannot be fully appreciated by standard deviation of returns

Forecast Accurac	cy Measure	Formula		Description
Mean Square Error	MSE	$MSE = \frac{\sum (F_t - Y_t)^2}{n} $ (4)	4)	Forasmuch any error is being raised with the square. So this way highlights the significant error values. This feature is quite significant because forecasting methods with approximations of bias are frequently more suitable than the method which gives not only negligible errors but significant.
Mean Absolute Deviation	MAD	$MAD = \frac{\sum F_t - Y_t}{n} \tag{5}$	5)	It is similar to standard deviation but the formula of estimation is less difficult to apply for time series. The usage is advisable when the fore- cast bias must be estimated using the same evaluation units as forecast factor is evaluated.
Mean Forecast Error	MFE	$MFE = \Sigma(F_t - Y_t) \qquad (\epsilon$	6)	Very often it is very important to estimate whether the forecast method has a systematic error i.e. the present forecast value is always major (or minor) than time series value. In this case the mean forecast error is being used. If the systematic bias does not exist the MFE value will be equal to zero. If the forecast value is signally negative the forecast method overestimates trend series. If the systematic bias is signally posi- tive the forecast method generates major values than time series.
Mean Absolute Percentage Error	MAPE	$MAPE = \frac{1}{n} \sum \left \frac{F_t - Y_t}{Y_t} \right \qquad (7)$	7)	The Mean Absolute Percentage Error is useful when assessing the fore- cast error an important factor is the estimated value. MAPE estimates the size of bias comparing with time series values. This fact is very important when the times series value is quite large.
Tracking Signal	TS	$TS = \frac{\sum (F_t - Y_t)}{MAD} \tag{8}$	8)	Tracking signal is the method to control the forecast accuracy. New data is compared with forecast time series and adequacy is evaluated.

Table 1. Forecast Accuracy Measures

(Pečiulis, Šiaudinis 1997). Risk is defined as the probability that the actual profit or return on investment will deviate from the expected size (Norvaišienė 2005). With the purpose to minimize risk, researchers use modern methods of statistics and probability theory. One of them is the Stock price correlation method described by Rutkauskas, Damašienė (2002). Correlation can be described as a parameter of some stochastic processes which are used to model variations in financial asset price. Financial asset prices exist now and are observed in the past but it is not possible to determine exactly what prices will be in the future. Correlation is a measure of co-movements between two return series (Alexander 2001). This method is relevant to indexes because if the correlation ratio is negative (R<0), the trend of total stocks (indexes) is linked to decrease compared to another (main) index. To select an appropriate investment tool, modern portfolio theory suggests using the Capital Assessment Pricing Model (further - the CAPM). The CAPM is one of the methods to calculate the profitability or the risks. The CAPM provides the link between each security and risk profitability. When in the market the equilibrium exists, the expected stock returns are proportional to systematic risk, which is inevitable even diversifying the portfolio. The relationship between the proposed securities and profitable systematic risk can be evaluated by the CAPM, proposed by William Sharpe in 1960.

Variable β determines price changes of a stock or other security in the portfolio in comparison with the stock

market prices. B coefficient indicates a systematic risk. In market countries β is calculated on the assumption that the total financial asset portfolio is described by the various markets indexes (Gaidienė 1995). Using this methodology, the required yield is calculated on the basis of a risk indicator expressed in β :

$$k_{r(j)} = k_{rf} + \beta_{(j)} (k_M - k_{rf}), \qquad (9)$$

where $k_{r(j)}$ is preferred return rate of the *j* security, k_{rf} is risk-free profit level, $\beta_{(j)}$ is beta coefficient representing the *j* security risk, k_M is market return rate, $k_M - k_{rf}$ is market risk premium.

According to this model, the desired rate of return is calculated as the risk-free rate of profit and risk premium, systematic assessment of security risk (Norvaišienė 2005). According to the CAPM, risk level of each index will be calculated using (3) formula and it will describe the systematic risk as OMXBBPI includes the same companies' stocks as industry indexes do and involves a part or each index risk.

The other method which is more complicated to identify the level of risk is the analysis of the distribution of index returns using Chi-Squared Test technique (Pukėnas 2005):

$$\chi^{2} = \sum_{i=1}^{k} \frac{(O_{i} - E_{i})^{2}}{E_{i}}, \qquad (10)$$

where: O_i – current frequencies, E_i – expected frequencies, k – the range of variables.

Calculated theoretical frequencies coincide with a number of empirical frequencies. From here there is a necessity to compare empirical frequencies and calculated or expected frequencies so that they would establish reliability or contingency of a divergence observed between them.

3. Description of the index and industries

Benchmark index (OMX Baltic Benchmark) is one of indexes of OMX Baltic index family. It is available in the Baltic region. The index consists of a portfolio of the largest in the capitalization and most liquid companies of shares traded on the OMX Baltic Stock exchanges. Company stock weight in the index depends on the company's stock market value and number of stock in the market, i.e. the index includes only the share capital, which circulates freely in the market. So it will be particularly useful for OMXBB investment products as controllers and comparative index for investors. For the Price index (PI) such as mentioned in the article, dividends are not evaluated (not deducted). Thus, the price index only reflects the constituent stock price movements. The industry indexes cover the entire Baltic securities market. They are based on the GICS classification standard. GICS is an international classification created to meet investors' demand for more accurate, more comprehensive, standardized classification. Industry indexes indicate trends in the sector and allow comparing the same industry companies. The indexes include all Baltic Stock exchanges and the Official Secondary trading list of the companies. They are counted separately for each GICS sector.

In this research we use daily data and our sample includes stock market close prices of 11 indexes: OMX Baltic Benchmark PI (Baltic States) and all industry indexes (Table 2).

Information on local daily prices was found on the stock market's respective websites. We source data for the same periods. The data is for the 01/01/2000-30/12/2009 period.

In this stage of the research the hypothesis No. 1 (H1) arises: whether the industry index share of the basic composition of the index affects the strength of the relationship between industry index and index OMXBBPI.

For this purpose the share of each industry index was calculated (Fig. 1).

Table 2. Forecast objects

	OMX Baltic Index Group									
OMX Baltic Bench- mark PI	OMX Baltic Energy	OMX Baltic Ma- terials	OMX Baltic Industrials	OMX Baltic Consumer Discretionary	OMX Baltic Con- sumer Staples					
OMXBBPI	OMXB10PI	OMXB15PI	OMXB20PI	OMXB25PI	OMXB30PI					
OMX Baltic Bench- mark PI	OMX Baltic Health Care	OMX Baltic Finan- cials	OMX Baltic Informa- tion Technology	OMX Baltic Telecommu- nication Services	OMX Baltic Utilities					
OMXBBPI	OMXB35PI	OMXB40PI	OMXB45PI	OMXB50PI	OMXB55PI					

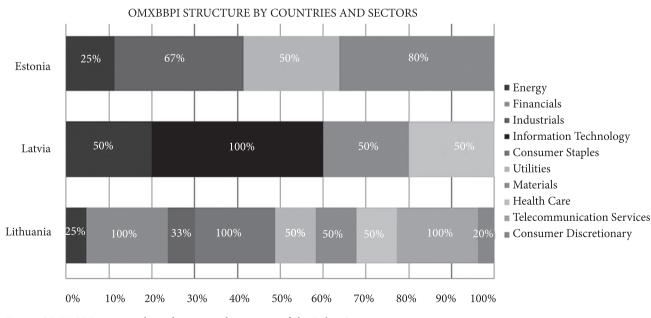


Fig. 1. OMXBBPI structure by industries and countries of the Baltic States

Table 3. The relationship between OMXBBPI and industry indexes and their share (%)

	OMXBBPI correlation ratio	% share in the index
OMXB10PI	0.9680	12.90%
OMXB15PI	0.8782	12.90%
OMXB20PI	0.9754	19.35%
OMXB25PI	0.9737	3.23%
OMXB30PI	0.9706	12.90%
OMXB35PI	0.9155	6.45%
OMXB40PI	0.9825	6.45%
OMXB45PI	-0.2816	6.45%
OMXB50PI	0.6762	3.23%
OMXB55PI	0.9186	16.13%
Correlation ratio	0.3074	-

Table 4. Index returns' correlation ratios

	OMX	B10PI	B15PI	B20PI	B25PI	B30PI	B35PI	B40PI	B45PI	B50PI	B55PI
OMX	1.0000										
B10PI	0.4011	1.0000									
B15PI	0.2520	0.2046	1.0000								
B20PI	0.6004	0.2359	0.1932	1.0000							
B25PI	0.6336	0.2604	0.2180	0.4781	1.0000						
B30PI	0.3617	0.2093	0.2202	0.2828	0.3446	1.0000					
B35PI	0.2612	0.1826	0.1440	0.1760	0.2162	0.1960	1.0000				
B40PI	0.7262	0.3074	0.2221	0.3616	0.4468	0.2733	0.2477	1.0000			
B45PI	0.1305	0.1102	0.1056	0.1312	0.1002	0.1277	0.0856	0.1227	1.0000		
B50PI	0.6613	0.1767	0.1256	0.3131	0.3356	0.1761	0.1092	0.3205	0.0523	1.0000	
B55PI	0.2789	0.1794	0.1227	0.1713	0.1998	0.1841	0.1207	0.1876	0.0561	0.1894	1.0000

Table 5. Index returns' descriptive statistics

Statistics	\overline{x}	min	max	σ	σ^2	Skewness	Kurtosis
OMX	0.04%	-8.44%	9.38%	0.0110	0.0001	0.1091	120.109
B10PI	0.05%	-16.56%	12.22%	0.0160	0.0003	-0.4763	116.504
B15PI	0.01%	-12.68%	16.37%	0.0185	0.0003	0.3868	90.592
B20PI	0.03%	-8.51%	10.10%	0.0144	0.0002	-0.1975	46.610
B25PI	0.04%	-11.17%	9.83%	0.0139	0.0002	-0.2786	85.154
B30PI	0.03%	-6.31%	12.81%	0.0114	0.0001	0.4813	118.122
B35PI	0.09%	-42.86%	12.31%	0.0215	0.0005	-42.383	808.476
B40PI	0.07%	-12.94%	14.08%	0.0178	0.0003	0.2294	141.020
B45PI	-0.04%	-29.99%	37.04%	0.0277	0.0008	0.9122	263.344
B50PI	0.00%	-11.04%	25.34%	0.0145	0.0002	22.017	455.150
B55PI	0.09%	-56.56%	19.91%	0.0222	0.0005	-56.995	1.743.122

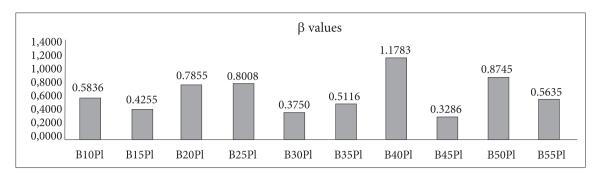


Fig. 2. Index β coefficient values (risk evaluation)

As it is seen in Fig. 1, Lithuanian companies predominate (51.61%) in OMXBBPI composition. Major part of the index consists of OMXB20PI Industrials (19.35%), OMXB25PI Consumer Discretionary (16.13%), OMXB10PI Energy (12.90%), OMXB15PI Financials and OMXB30PI Consumer Staples (each 12.90%). OMXBBPI is the most diversified by Lithuanian companies, and least by Latvian and Estonian.

Evaluated correlation ratio determines the relationship strength among all indexes (Table 3) and rejects the H1.

80% of the industry indexes have a link with the main OMXBBPI index (R>0.9). A rather weak form of the relationship is with telecommunications sector index which is 0.6762, while the Information Technology index has opposite direction trend and the effect is very low in the basic index -0.2816. H1 must be rejected because the investigation revealed that different indexes, representing part of the same index OMXBBPI have different degrees of impact on the main index. For example, OMXPBI35, OMXB40PI and OMXB50PI each makes 6.45% of the OMXBBPI composition, but their correlation coefficients are -0.2816 and 0.9825 respectively. The relationship among index returns (Table 4) once again determines that H1 should be rejected.

In all cases the relationship is quite weak and indexes do not influence each other.

OMXB45PI and OMB55PI markets are more profitable but the risk level is high (Table 5). This proposition is based on standard deviation – 0.0277 and 0.0222 respectively, while investment into OMXBBPI and OMB30PI index stocks generates less losses and lower profitability level – respectively 0.0110 and 0.0114 evaluating the return standard deviation. We have tested all indexes described in Section 2. In all cases *p*-value is higher than the significance level is, so there is no significant difference between the two methodologies for analysis: theoretical and empirical. β parameter is the main indicator of the CAPM, it shows the systematic risk level. All tested

indexes include systematic risk, only its level is different (Fig. 2). Non-systematic risk level varies from -0.005 to 0.0007, so it is nearly equal to zero. This means that nonsystematic risk does not exist. Investors take a greater level of the risk investing into B40PI (1.1783), B50PI (0.8745), B25PI (0.8008). The lower risk level is related to the investments into B30PI (0.3750), B45PI (0.3286) and B15PI (0.4225). So the research results imply that systematic risk exists in all industry stock markets, only the degree of risk varies. If to choose standard deviation as a risk measure, then using the highest level of the investment risk is taken in such markets as B40PI ($\sigma = 293940.02$), B35PI ($\sigma = 188877.4195$), B55PI ($\sigma = 121693.2415$). The lowest value of the deviation which reflects the risk level are B15PI (σ = 3438.9633), B50PI (415.7623). This difference can be explained by standard deviation and β evaluation methodological difference because the first describes the fluctuation of index or return trend and it shows the common risk trends.

4. The results of forecasting using the EMA

This paper is focused on one of TA indicators - the exponential moving average rule (further - the EMA) and the possibility to use this method for market fluctuation signals. The methodology disassociates from particular buy-and-sell strategies and specific rules of application. It excludes transaction costs and fees, dividends are not paid (D = 0). In this stage of the research hypothesis No. 2 arises: whether the EMA has a predictable power on market fluctuation signals. Longer period of the EMA means higher bias level and less accurate forecast of prices but it does not mean that the EMA is not suitable to predict stock market fluctuations. All applied accuracy measures differ for forecasting industry indexes (Table 6). For specific indexes separate EMA lengths differ by forecasting accuracy level. This demonstrates MSE values. In particular markets this indicator provides lower or higher bias level.

T 1		MSE			MAD		
Index	Min	Max	R	Min	Max	R	
OMXBBPI	1.6621	1225.7970	0.9930	8.7018	268.7274	0.9948	
OMXB10PI	3.0194	1126.2233	0.9976	10.3737	234.3422	0.9909	
OMXB15PI	0.6544	255.9466	0.9959	13.5605	325.8130	0.9940	
OMXB20PI	1.6067	1018.8959	0.9944	13.0732	373.7323	0.9957	
OMXB25PI	6.0231	4102.9815	0.9924	14.0097	429.6435	0.9966	
OMXB30PI	1.1114	768.3996	0.9941	9.2630	245.0824	0.9934	
OMXB35PI	32.3703	12511.1941	0.9979	12.4236	344.9284	0.9953	
OMXB40PI	23.3740	14266.0530	0.9950	15.4866	455.2855	0.9966	
OMXB45PI	1.7379	533.0337	0.9973	131.1743	2914.7334	0.9927	
OMXB50PI	0.1799	46.9391	0.9972	8.8081	172.3010	0.9741	
OMXB55PI	14.3340	4076.4000	0.9978	8.9603	196.4084	0.9905	
x 1		MFE		МАРЕ			
Index	Min	Max	R	Min	Max	R	
OMXBBPI	-1.9284	-0.0230	-0.9961	0.0026	0.0785	0.9946	
OMXB10PI	-2.9640	-0.0302	-0.9983	0.0037	0.0798	0.9881	
OMXB15PI	0.0013	0.3593	0.9568	0.0041	0.1111	0.9964	
OMXB20PI	-0.5268	-0.0088	-0.9589	0.0036	0.1060	0.9972	
OMXB25PI	-2.2898	-0.0263	-0.9980	0.0033	0.1047	0.9983	
OMXB30PI	-1.4507	-0.0165	-0.9952	0.0027	0.0742	0.9964	
OMXB35PI	-7.7225	-0.0783	-0.9996	0.0045	0.1137	0.9963	
OMXB40PI	-5.6418	-0.0606	-0.9996	0.0039	0.1246	0.9982	
OMXB45PI	0.0167	1.3688	0.9935	0.0054	0.1374	0.9968	
OMXB50PI	0.0061	1.0234	0.9895	0.0032	0.0665	0.9794	
		1	İ			İ	

Table 6. Accuracy measures

MSE of forecasted values of B35PI and B40PI indexes are characterized by large swings. Wherewith the EMA is longer, MSE value is ipso facto higher. This tendency dominates in all markets. So it means that the Exponential Moving Average, which covers a longer period, generates more inaccurate value F_t . The EMA provides the best results in B50PI market: min_{MSE} = 0.1799, max_{MSE} = 46.9391. This means that forecasted values are the closest to the actual ones and bias level is quite low in comparison with the other forecasted indexes. MAD as a forecast accuracy measure implies that the EMA is suitable to forecast B50PI prices. Minimum and maximum values of MAD are the lowest compared to the other indexes.

MFE for P50PI is nearly equal to zero with the higher constant level and is equal to 1.0234 when n = 100. Although telecommunication industry stocks have the smallest share in OMBBPI structure, this index forecasts were the most accurate.

Trying to determine whether the selected forecasting method has a systematic bias, the Mean Forecasting Error

was evaluated. Inasmuch as the MSE value of B15PI index forecast is 0.0013 and nearly zero, then the systematic bias does not exist. There are some negative average values of MSE in tested markets which indicate that in OMBBPI index stock market the forecasted values are being overvalued. This fact can be explained by correlation ratio among OMXBBPI and industry indexes. In all cases the relationship strength between n parameter and forecast accuracy measures such as MSE, MAD, MFE, MAPE is strong (R>0.97) (Table 7). If R>0.9 then values of related indexes are overvalued. The least overvalued (or not overvalued) are such indexes as OMXB15PI (R = 0.8782), OMXB45PI (R = -0.2816) and OMXB50PI (R = 0.6762). It leads to a conclusion that in all markets except OMXB15PI, OMXB45PI and OMXB50PI systematic errors exist in forecasting the stock prices using the EMA.

Since the time series values are quite high, the MAPE was assessed. This method highlights a part of systematic error comparing with the whole time series. In all cases MAPE is \in (0;1). The longer period influences the EMA is covering, the higher MAPE is. This trend is confirmed in all markets, only the degree of precision varies from 97.94% to 99.83%.

The graphical and bias analysis showed that the EMA is suitable to predict market fluctuations so H2 is accepted.

The hypothesis No. 3 arises after H2 is accepted: which period EMA helps to generate market fluctuations signals? Tracking signal (further TS) is a suitable method to control forecast accuracy and to find out exclusive EMA periods to predict market fluctuations. Using this method it was noticed that TS changes its trend when a specific EMA is applied (Table 7).

During the research it appeared that only certain period EMA can forecast the stock market fluctuations. There are common periods of EMA for each index: 48, 49, 50 days; 92, 93, 94 days. Every index needs some groups of additional period EMA.

To determine whether these EMAs work it is necessary to perform graphical analysis (Fig. 3). The analysis shows that when EMA value is higher than the real index value, index has a trend to fall down and vice versa, lower EMA value is related to the market growth. The largest OMX stock market fluctuations such as financial crisis of 2008–2009 are as a result of all forecasted the majority of different periods of EMA intersections. In this context a new problem arises: whether a mix of technical and functional analysis is a powerful tool to predict financial market bubbles. The research of the issue will be provided in a new study based on fundamental analysis issues and its further comparison with previous studies.

The EMA forecast results of the Baltic States stock market show the main trends of market development and investors' activity.

5. Empirical results and conclusions

This study is the first academia research of technical analysis usage to predict the stock market fluctuations for OMX Baltic Benchmark Index and Industrial indexes using exponential smoothing method. A significant part of semiprofessional traders use technical analysis as a method to forecast stock prices, but no researches in the Baltic States confirmed or refused the statistical validity of this method usage for predicting strong stock market fluctuations too.

EMA method is relevant to forecast stock market fluctuations of OMX index in the Baltic States. The research claims that for each index an appropriate EMA length should be found. So, it is 48–50, 48–70, 72–74, 92–94 days. The length differs from the EMA length mentioned in previous researches made by Academia on the global level. The correlation analysis showed that all industrial indexes mentioned in this study except OMXBPI45 have a strong dependence on the main OMX index.

As Lithuanian companies are predominant (51.61%) in OMXBBPI composition, in-depth analysis of Lithuanian companies' performance should be involved in evaluating the stock market conditions and predicting trends and fluctuations. 80% of the industrial indexes have a link with the main OMXBBPI index (R > 0.9) so industry analysis should be also involved in the analysis trying to predict further stock market development scenario. OMXB45PI and OMB55PI markets are most risky and this proposition is based on standard deviation - 0.0277 and 0.0222 while OMXBBPI and OMB30PI are the least risky - 0.0110 and 0.0114 respectively, evaluating the return standard deviation. Due to the risk level all forces which had an impact on these indexes should be identified. In all cases *p*-value is higher than the significance level is, so there is no significant difference between the two methodologies for analysis: theoretical and empirical.

 β parameter is the main indicator of CAPM and displays the systematic risk level. All tested indexes include systematic risk, only its level is different. Non-systematic risk level varies from -0.005 to 0.0007 and it is about zero. This means that non-systematic risk does not exist.

OMX	Length	Value	Length	Value	Length	Value	Length	Value	_	
∆ n−1	48	16.8919	72	17.9785	92	18.5585	68	17.8225		
n	49	17.8924	73	18.3045	93	16.7860	69	17.5205		
Δ n+1	50	17.0239	74	18.0503	94	17.0941	70	17.9050		
B10	Length	Value	Length	Value	Length	Value	Length	Value	_	
∆ n–1	48	26.3956	72	29.7238	92	31.7560	68	29.2435		
n	49	27.4999	73	30.1584	93	29.9830	69	28.9133		
∆ n+1	50	26.7611	74	29.9486	94	30.3801	70	29.4855		
B15	Length	Value	Length	Value	Length	Value	Length	Value	Length	Value
Δ n–1	48	-1.2942	72	-1.6810	92	-1.6872	68	-1.6458	81	-1.627
n	49	-0.5737	73	-1.5041	93	-2.9569	69	-1.8497	82	-1.625
∆ n+1	50	-1.3271	74	-1.6611	94	-2.7588	70	-1.6735	83	-1.628
B20	Length	Value	Length	Value	Length	Value	Length	Value		
Δ n-1	48	3.9030	72	3.8013	92	3.6671	54	3.9257	_	
n	49	4.5725	73	4.0022	93	2.4339	55	3.9262		
Δ n+1	50	3.9164	74	3.7921	94	2.6372	56	3.9250		
B25	Length	Value	Length	Value	Length	Value			_	
Δ n-1	48	12.9816	72	13.2992	92	13.6572	_			
n	49	12.4433	73	13.4938	93	12.6594				
Δ n+1	50	12.4940	74	13.3594	94	12.8315				
B30	Length	Value	Length	Value	Length	Value	_			
Δ n-1	48	-0.8090	72	-1.0331	92	-1.1431	_			
n	49	-0.7337	73	-1.0938	93	-1.2483				
Δ n+1	50	-0.8259	74	-1.0489	94	-1.2375				
B35	Length	Value	Length	Value	Length	Value	_			
Δ n-1	48	48.5003	72	53.5490	92	56.4880	_			
n	49	49.4215	73	53.8904	93	55.6796				
∆ n+1	50	49.0251	74	53.8399	94	55.9748				
B40	Length	Value	Length	Value	Length	Value	_			
∆ n–1	48	27.4799	72	30.4082	92	31.5226	_			
n	49	28.1769	73	30.6541	93	30.5253				
Δ n+1	50	27.8325	74	30.5571	94	30.7368				
B45	Length	Value	Length	Value	Length	Value	Length	Value	_	
Δ n-1	48	27.4799	72	30.4082	92	31.5226	39	-0.7431	_	
n	49	28.1769	73	30.6541	93	30.5253	40	-0.6832		
Δ n+1	50	27.8325	74	30.5571	94	30.7368	41	-0.7549		
B50	Length	Value	Length	Value	Length	Value			_	
Δ n-1	48	-7.7923	72	-11.6259	92	-13.1034	_			
n	49	-6.5802	73	-11.3281	93	-15.3713				
Δ n+1	50	-8.1394	74	-11.8352	94	-15.0900				
B55	Length	Value	Length	Value	Length	Value	_			
Δ n-1	48	91.1323			92	116.1590	_			
n	49	92.8870			93	116.5919				
Δ n+1	50	92.6323			94	115.1471				

Table 7. Specific EMA n periods

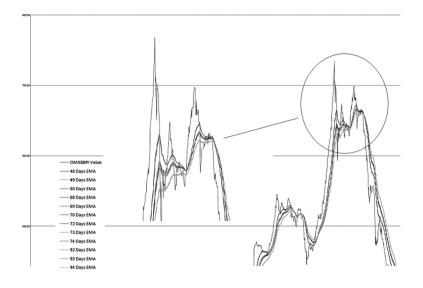


Fig. 3. Graphical analysis of the EMA forecasting results

The most risky indexes are B40PI (1.1783), B50PI (0.8745), B25PI (0.8008). The least risky indexes are (B30PI), B45PI (0.3286) and B15PI (0.4225). So the research result is simply that systematic risk exists in all industry stock markets, only the degree of risk is various.

In all cases the relationship strength between n parameter and forecast accuracy measures such as MSE, MAD, MFE, MAPE is strong (R>0.97). The longer EMA means higher bias level and less accurate forecast to predict prices, but it does not mean that EMA is not suitable to predict stock market fluctuations.

The suggestion to use EMA method instead of SMA method (see previous studies of Dzikevicius, Saranda, Kravcionok 2010) was confirmed once again by descriptive statistics in each case. If the standard deviation reflects the risk of the index, it means that EMA method is less risky to use for estimating absolute error level.

It seems that EMA method is more suitable to predict stock market fluctuations rather than short moving average.

Summarizing the study, exponential smoothing method is appropriate to indicate the fluctuations of stock markets in OMX Baltic Benchmark index market. It should be noted that during the research it provided the closest forecast values to the real index values because the higher weight is ensured to real historical prices of the previous day.

References

- Alexander, C. 2001. Market Models: A Guide to Financial Data Analysis. New York: John Wiley & Sons.
- Aniūnas, P.; Nedzveckas, J.; Krušinskas, R. 2009. Variance covariance risk value model for currency market, *Inzinerine Ekonomika – Engineering Economics* 1(161): 18–27.
- Barkoulas, J. T.; Baum, C. F.; Travlos, N. 2000. Long Memory in the Greek Stock Market, *Applied Financial Economics* 2(10): 177–184. doi:10.1080/096031000331815

- Bessembinder, H.; Chan, K. 1995. The profitability of technical trading rules in the Asian stock markets, *Pacific-Basin Finance Journal* 3: 257–284. doi:10.1016/0927-538X(95)00002-3
- Bokhari, J.; Cai, C.; Hudson, R.; Keasey, K. 2005. The predictive ability and profitability of technical trading rules: does company size matter?, *Economics Letters* 86: 21–27. doi:10.1016/j.econlet.2004.03.037
- Brock, W.; Lakonishock, J.; LeBaron, B. 1992. Simple technical trading rules and the stochastic properties of stock returns, *Journal of Finance* 47: 1731–1764. doi:10.2307/2328994
- Caginalp, G.; Balenovich, D. 2003. A theoretical foundation for technical analysis, *Journal of Technical Analysis* 59: 5–22.
- Dudzevičiūtė, G. 2004. Vertybinių popierių portfelio sudarymas ir vertinimas [Securities portfolio construction and evaluation], *Verslas: teorija ir praktika* [Business: Theory and Practice] 5(3): 116–124.
- Dzikevičius, A. 2004. Vertinimo, koreguoto pagal riziką, metodikų palyginamoji analizė, *Vagos* 64(17): 97–103.
- Dzikevicius, A.; Zamzickas, M. 2009. An Overview of Financial Crisis in U.S., *Economics and Management* 14: 166–172.
- Dzikevicius, A.; Saranda, S.; Kravcionok, A. 2010. The accuracy of simple trading rules in stock markets, *Economics and Management* 15: 910–916.
- Edwards, R.; Magee, J. 1992. *Technical Analysis of Stock Trends*. New York: New York Institute of Finance.
- Gaidienė, Z. 1995. *Finansų valdymas* [Finance management]. Kaunas: Pasaulio lietuvių kultūros, mokslo ir švietimo centras.
- Girdzijauskas, S., et al. 2009. Ekonominių burbulų susidarymas ir galimybės jų išvengti [Formation of economic bubbles: causes and possible preventions], *Technological and Economic Development of Economy* 15(2): 267–280. doi:10.3846/1392-8619.2009.15.267-280
- Ito, A. 1999. Profits on technical trading rules and time-varying expected returns: Evidence from Pacific-Basin equity markets, *Pacific-Basin Finance Journal* 7(3/4): 283–330. doi:10.1016/S0927-538X(99)00008-6

- Jorion, P. 2003. *Financial risk management*. New York: John Wiley & Sons.
- Juozaitienė, L. 2007. *Įmonės finansai: analizė ir valdymas* [Corporate finance: analysis and management]. Šiauliai: Šiaulių universiteto leidykla.
- Jurevičienė, D. 2008. *Asmeninių finansų pagrindai* [Personal finance basics]. Vilnius: Technika.
- Kannan, K. S.; Sekar, P. S.; Sathik, M. M.; Arumugam, P. 2010. Financial Stock Market Forecast using Data Mining Techniques, *International Multi Conference of Engineers and Computer Scientists* 1: 555–559.
- Klimavicienė, A.; Jurevičienė, D. 2007. Asmens investicijų į finansines priemones plėtros galimybės Lietuvoje [Personal investment in the financial arrangements for the development possibilities in Lithuania], *Verslas: teorija ir praktika* [Business: Theory and Practice] 8(1): 33–43.
- Lo, A. W.; Mamaysky, H.; Wang, J. 2000. Foundations of technical analysis: computational algorithms, statistical inference, and empirical implementation, *Journal of Finance* 55(4): 1705–1765. doi:10.1111/0022-1082.00265
- Lönnbark, C.; Soultanaeva, A. 2009. Profitability of technical trading rules on the Baltic stock markets, *Umeå Economic Studies* 761: 1–5.
- Marshall, B. R.; Qian, S.; Young, M. 2008. Is Technical Analysis Profitable On U.S. Stocks With Certain Size, Liquidity Or Industry Characteristics?, *Applied Financial Economics* 19(15): 1213–1221. doi:10.1080/09603100802446591
- Makridakis, S. G.; Wheelwright, S. C.; Hyndman, R. J. 1998. Forecasting: Methods and Application. 3rd ed. New York: John Wiley & Sons.
- Metghalchi, M.; Glasure, Y.; Garza-Gomez, X.; Chen, C. 2007. Profitable technical trading rules for the Austrian stock market, *International Business & Economics Research Journal* 9(6): 49–58.
- Mizrach, B.; Weerts, S. 2007. Highs and lows: a behavioural and technical analysis, *Applied Economics* 19: 767–777.

Myers, T. 1989. The Technical Analysis Course. Chicago: Probus. Norvaišienė, R. 2005. Imonės investiciju valdymas [Enterprise

- investment management]. Kaunas: Technologija. Pabedinskaitė, A. 2006. *Kiekybiniai sprendimų metodai. Koreliacinė regresinė analizė. Prognozavimas* [Quantitative decision making methods. Forecasting]. Vilnius: Technika.
- Parisi, F.; Vasquez, A. 2000. Simple technical trading rules of stock returns: Evidence from 1987 to 1998 in Chile, *Emerging Markets Review* 1: 152–164. doi:10.1016/S1566-0141(00)00006-6
- Pečiulis, S.; Šiaudinis, S. 1997. Įvadas į vertybinių popierių rinką [Introduction to the stock market]. Vilnius: Lietuvos bankininkystės, draudimo ir finansų institutas.
- Pilinkienė, V. 2008. Selection of Market Demand Forecast Methods: Criteria and Application, *Inzinerine Ekonomika – Engineering Economics* 3(58): 19–25.
- Pring, M. 1993. *Martin Pring on Market Momentum*. Gloucester: Probus Professional Pub.
- Pukėnas, K. 2005. Sport research data analysis with SPSS program. Kaunas: Lietuvos kūno kultūros akademija.
- Račickas, E.; Vasiliauskaitė, A. 2010. Global financial crisis and its impact on Lithuanian economy, *Management and Economics* 15: 1006–1017.
- Ratner, M.; Leal, R. 1999. Tests of technical trading strategies in the emerging equity markets of Latin America and Asia, *Journal of Banking and Finance* 23(12): 1887–1905. doi:10.1016/S0378-4266(99)00042-4
- Rutkauskas, A. V.; Damašienė, V. 2002. Finansų valdymas [Finance management]. Šiauliai: Šiaulių universiteto leidykla.
- Rutkauskas, A. V.; Martinkutė, R. 2007. Investicijų portfelio anatomija ir valdymas [Investment portfolio anatomy and management]. Vilnius: Technika. doi:10.3846/1371-M
- Taylor, M. P.; Allen, H. 1992. The use of technical analysis in the foreign exchange market, *Journal of International Money and Finance* 11: 304–314. doi:10.1016/0261-5606(92)90048-3
- Tillson, T. 1998. Smoothing techniques for more accurate signals, Stocks & Commodities 16(1): 33–37.

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