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# FORMATION OF AN INTEGRATED STOCK PRICE FORECAST MODEL IN LITHUANIA

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**Abstract.** Technical and fundamental analyses are widely used to forecast stock prices due to lack of knowledge of other modern models and methods such as Residual Income Model, ANN-APGARCH, Support Vector Machine, Probabilistic Neural Network and Genetic Fuzzy Systems. Although stock price forecast models integrating both technical and fundamental analyses are currently used widely, their integration is not justified comprehensively enough. This paper discusses theoretical one-factor and multi-factor stock price forecast models already applied by investors at a global level and determines possibility to create and apply practically a stock price forecast model which integrates fundamental and technical analysis with the reference to the Lithuanian stock market. The research is aimed to determine the relationship between stock prices of the 14 Lithuanian companies listed in the Main List by the Nasdaq OMX Baltic and various fundamental variables. Based on correlation and regression analysis results and application of c-Squared Test, ANOVA method, a general stock price forecast model is generated. This paper discusses practical implications how the developed model can be used to forecast stock prices by individual investors and suggests additional check measures.

**Keywords:** Stock price, forecast, correlation analysis, regression analysis, fundamental analysis, technical analysis, model, investment.

**JEL Classification:** G1, G12, G2, G30.

## 1. Introduction

Nowadays individual and institutional investors are surrounded by a rapidly changing external environment (political, social, economic and technological) which results in volatility in the financial markets. Inability to manage investments properly is considered to be one of the causes of the global 2008–2009 financial crisis.

Investments in securities, especially to companies' stocks, are the most common type of investments. However, investors, especially if they are individual persons, often lack knowledge needed to make investment decisions, which can lead to financial losses. If these investors could make more accurate stock price forecasts, financial resources could be allocated more effectively. If this were the case, the development of stock markets could result in increasing confidence among individual investors.

In order to forecast stock prices investors usually use either fundamental or technical analysis. Some investors may try to apply models which include both fundamental and technical analysis with a basis on neural networks. However, this requires a sophisticated understanding of neural networking.

The problem is that since global financial markets and economic have recovered after the financial crisis of 2008–2009, the academia started to pay less attention to research that focuses on stock markets and their forecasts. Several studies of high quality have been done to forecast stock prices, probably since it seemed attractive due to high benefits (Zavadskas, Turskis 2011; Li *et al*. 2014).

Research aimed to help investors in the application of both fundamental and technical analysis without using neural networks is at early development phase. Due to this reason a stock price forecast model which integrates both analyses is being developed and tested in the Lithuanian stock market with a possibility to apply it at global level further. It is assumed that stock prices in various foreign markets can be also predicted using the same stock price forecast model.

The purpose of this paper is to clarify if it is possible to form and practically apply a stock price forecast model with reference to previously conducted research based on technical analysis and possibilities to apply financial ratio analysis when forecasting stock prices.

Moving Average (MA), one of the widely used technical analysis tools, is not useful when forecasting stock price movement trends. For specific time series its lengths differ by forecast accuracy level. Thus this method can generate significant forecast value errors and deviations from real stock prices.

Meanwhile, Exponential Moving Average (EMA) with an appropriate α Constanta level is more relevant to forecast stock prices. The highest α level decreases the probability of a higher bias level for investors. However, longer period of the EMA means higher bias level and less accurate forecast of stock prices but it does not mean that this method is unsuitable to predict stock markets fluctuations.

Previous research proves that a company analysis should be conducted, after that a sector analysis and then an economic analysis should be conducted. By so doing the links between the company and the external factors can be identified and used to evaluate their impact on the financial company's performance and its stock prices. That's why it is necessary to obtain various variables (macroeconomic factors, financial ratios, sector indexes etc.) which potentially have an influence on companies' stock prices. This can help in the investment decisions making.

## 2. Review of theoretical stock price forecast methods and models

While most investors believe that markets in general, and stock markets in particular, will deliver increased value in the future, during times of economic and financial instability they face significant losses. Most investors relate their expectations to increasing asset value, supported by future profit, productivity, population growth and similar factors. The global financial and economic crisis of 2008–2009 demonstrated that investors' false belief in unstoppable asset value growth is the main reason for the financial market downturn.

Today econometric and economic science make possible the application of various methods and models aimed at predicting stock market processes but not all of already available theoretical forecast methods and models can be applied effectively.

For instances, in Lithuania, the most common methods used are quite simple, namely, fundamental and technical analysis.

Fundamental analysis is based on the in-depth analysis of companies' financial performance, surrounding industrial environment, macroeconomic factors, as well as industrial news. All this supports decision making when forecasting stock prices (Chen 2013). Its application also requires the assessment of companies' future growth prospects and competitive landscape (Bonga 2015) as well as potential changes in GDP, sales strategies and other different indicators relevant not only for individual businesses but for the industries as a whole in which they operate (Kartašova, Venclauskienė 2014). In order to forecast stock prices the Residual Income Model (RIM) with its strong theoretical background can be applied with reference to the financial data sourced from accounting (Sarikhani, Ebrahimi 2012; Tareq 2012; Kariuki, Oyugi 2013). As Higgins (2011) states, its successful application contributes to a fundamental perspective when making decisions regarding forecast of stock prices.

Proponents of technical analysis criticize the application of fundamental analysis by claiming that the stock market historical data creates problematic assumptions for the development of rules used to predict future changes in stock prices (Kimoto *et al*. 1990; Olson, Mossman 2003). Indeed, investors sometimes ignore fundamental analysis and rely solely on technical analysis results. In their opinion, application of fundamental analysis is useful for a long-term investment while in the short-term it may generate losses.

For instance, Autoregressive and Moving Average (ARMA) model is widely used by the proponents of technical analysis. Autoregressive Integrated Moving Average (ARIMA) as an improved ARMA model can be also used effectively when forecasting stock prices. The main difference between the models is that ARIMA model converts a non-stationary data to a stationary data before its application. ARIMA model is widely used to make linear data series forecasts (Box, Tiao 1975). Mondal *et al*. (2014) claim that the accuracy of stock price forecasts achieved with ARIMA model is quite high i.e. above 85%, making the model suitable for practical use with a relatively small bias.

In addition to these methods and models aimed to support companies' stock price forecasts, other various methods and models exist. For instances, artificial neural networks

(ANN) method is widely applied (Öğüt *et al*. 2009; Tseng *et al.* 2012; Guersen *et al*. 2011; Mostafa 2010; Cheng *et al*. 2012; Cimpoeru 2011). Bildirici and Ersin (2009) also suggest to use an ANN-APGARCH model as an improved APGARCH model to make stock prices forecasts more accurate by reflecting the real situation in the market.

Data mining and Neuro Fuzzy system methods are based on a possibility of extracting useful information from various data sets and play an important part when forecasting stock markets and making investment decisions. These approaches are applied in order to monitor the entire the stock market price behavior and market fluctuations. Meanwhile, Markov Model is developed exclusively for financial markets and stock price forecasting (Preethi, Santhi 2012).

Sometimes integrated or hybrid models such as the hybrid model of artificial intelligent methods proposed by Wu *et al.* (2015) can be also be applied. It is a combination of ARMA, the support vector machine method (SVM) and a probabilistic neural network (PNN). Another offered model includes application of genetic fuzzy systems (GFS) and ANN (Hadavandi 2010).

Despite the fact that a lot of theoretical and practically tested stock price forecast methods and models exist, the majority of Lithuanian investors believe that stock prices can be described by one factor. For example, it is assumed that yields depend on the GDP and its dynamics (Duca 2007).

In 2011, Hsing proposed a stock price forecast model suitable for a global and most developed stock markets as well as less developed markets such as Lithuanian one. The model is based on an expansion of the previously proposed models (Bulmash, Trivoli 1991; Abdullah, Hayworth 1993; Kim 2003; Ratanapakorn, Sharma 2007; Humpe, Macmillan 2009; Pilinkus 2009, 2010).

Unfortunately, only few studies suggest a stock price forecast model that includes not only the fundamental factors but also the technical elements of the analysis. One such model has been proposed by Bettman *et al*. (2009). Ferreira and Santa-Clara (2008) reviewed the relevant academic literature and concluded that price multiples, macroeconomic factors, financial ratios and different measures of risk are the most common variables taken into account when forecasting stock returns. For example, Campbell and Shiller (1988), Lamont (1998) used the P/E ratio to forecast stock returns. This ratio enables an analysis of investors' willingness to pay for the company's earnings. It makes sense to purchase stocks with low P/E ratio value only in case if the earnings are real (Kartašova, Venclauskienė 2014). Meanwhile Kothari and Shanken (1997), Pontiff and Schall (1998) use the P/BV ratio.

Another financial ratio to forecast companies' stock prices suggested by the academia is return on equity (ROE) (Petcharabul, Romprasert 2014). It measures company's performance efficiency (Higgins 2009). Elleuch (2009) also noticed that the ratio is a predictive measure to forecast future stock prices. Omran and Ragab (2004) discovered that ROE plays a significant role in investment decision making.

Return on assets (ROA) ratio also indicates the level of company's performance (Purnamasari 2015).

Ball and Brown (1968), Hou *et al*. (2014) indicate that in addition to the mentioned financial ratios, earning per share ratio (EPS) may serve as a variable when forecasting stock prices. Analysts estimate that the stock price increases when reported ratio is higher than expected and vice versa – if it is lower, then the stock price decreases (Renfro 2015).

A company's net profit margin (NPM) is also an important driver of stock performance and price trends. Financial analysts and investors refer to earnings, as well as NPM, as stock price is often related to a company's expected future earnings (Amir *et al*. 2012). Due to this reason the ratio may serve as a useful variable when forecasting stock prices, for example in the Lithuanian market.

With the reference to previously conducted research, Dutta *et al*. (2012) concluded that financial ratios can used by investors to assess future performance of companies' stock prices and their trends.

Therefore, financial ratios can be also used by to classify the performance of different companies and forecast their stock prices in the market. Both linear and non-linear types of relationship between financial ratios and stock prices can be used as a background. This finding is also supported by Jabbari and Fathi (2014).

## 3. Research methodology

For the research purposes the annual data of 14 Lithuanian companies in accordance to the Baltic Main List of stocks for the period of 2010–2014 was used (Table 1).

Table 1. List of researched companies and the industries they operate in

| Symbol | Company's name | Industry |
|---|---|---|
| APG1L | Apranga | 5000 Consumer Services |
| CTS1L | City Service | 2000 Industrials |
| GRG1L | Grigiškės | 1000 Basic Materials |
| IVL1L | Invalda INVL | 8000 Financials |
| LDJ1L | Lietuvos dujos | 7000 Utilities |
| LNA1L | Linas Agro Group | 3000 Consumer Goods |
| PTR1L | Panevėžio statybos trestas | 2000 Industrials |
| PZV1L | Pieno žvaigždės | 3000 Consumer Goods |
| RSU1L | Rokiškio sūris | 3000 Consumer Goods |
| SAB1L | Šiaulių bankas | 8000 Financials |
| TEO1L | TEO LT | 6000 Telecommunications |
| UTR1L | Utenos trikotažas | 3000 Consumer Goods |
| VLP1L | Vilkyškių pieninė | 3000 Consumer Goods |
| VBL1L | Vilniaus baldai | 3000 Consumer Goods |

Only last (close) annual stock prices of the listed companies were analysed. Statistical data reflecting indexes provided in the Table 1 were also used. In order to reflect the real stock market performance dividends are reinvested in the gross index.

The relevant financial data for these companies is sourced from the officially published financial statements. Based on the in-depth literature analysis, seven financial ratios were selected for the further analysis (Table 2).

Table 2. Calculation methodology and description of the financial ratios used

| Financial ratio | Calculation methodology | Description |
|---|---|---|
| EPS (Earnings Per Share) | $\frac{\text{Net profit} - \text{Preference share dividend}}{\text{Weighted average number of ordinary outstanding}}$ | EPS ratio shows how much of the company's earned net profit is attributed to an ordinary share. |
| P/E (Price / Earnings Ratio) | $\frac{\text{Current share price}}{\text{Earnings per share}}$ | P/E ratio reflects how much an investor pays for 1 euro of the company's 1 net profit euro. It also relates the stock's market value to the profit reflected in financial statements. |
| P/S (Price to Sales Ratio) | $\frac{\text{Current share price}}{\text{Sales per share}}$ | P/S ratio shows how much an investor pays for 1 euro of sales revenue generated by one share. |
| P/BV (Price to Book Value Ratio) | $\frac{\text{Current share price}}{\text{Book value per share}}$ | P/BV reflects how much an investor pays for 1 euro of equity. |
| ROE (Return on Equity) | Net profit margin x Total assets turnover x $\frac{\text{Total assets}}{\text{Equity}}$ | ROE shows how much net profit is generated by 1 euro of equity. |
| ROA (Return on Assets) | Net profit margin x Total assets turnover | ROA shows how much net profit is generated by 1 euro of assets. |
| NPM (Net Profit Margin) | $\frac{\text{Net profit}}{\text{Sales}}$ | NPM indicates the percentage of net profit with 1 euro of sales revenue i.e. it shows the company's operating efficiency. |

The financial ratios are calculated in accordance with the methodology accepted by NASDAQ OMX.

Data indicating annual time series of macroeconomic factors is also used in this research. Based on the analysis of the scientific literature it was concluded that for this research purpose only the most important macroeconomic factors are analyzed. They are outlined as follows: Gross Domestic Product (GDP), value in EUR; Foreign Direct Investments (FDI), value in EUR; Consumer Price Indexes (CPI); Unemployment Rate (UR), %; Interest Rate of loans issued to households and non-financial institutions (IR), %; Import (I), value in EUR; Export (E), value in EUR.

Relevant data was sourced from the Official Statistics Portal and the Bank of Lithuania.

During the first phase of the research a data set combining companies' stock prices, financial ratios, macroeconomic variables, and sector indexes is built. The set is used to perform correlation analysis. Only variables which correlation with companies' stock prices $R \geq |0.95|$ are selected.

Further a regression analysis is conducted to equate a linear relationship between companies' stock prices and selected variables as well as analysis of variance (ANOVA).

For decision making purposes, additional measure of forecast accuracy evaluation is introduced. c-Squared Test is applied to check whether forecasted stock prices reflect real market prices.

To check whether forecasted companies' stock prices differ from the real ones, the analysis of the distribution of index returns using c-Squared Test method is used (1):

$$\chi^2 = \sum_{i=1}^{k} \frac{\left(O_i - E_i\right)^2}{E_i}, \tag{1}$$

where: $O_i$ – historical companies' stock prices; $E_i$ – forecasted companies' stock prices; $k$ – range of variables; Companies' stock price forecast model is acceptable when c-Squared Test p value >0.05. If this condition is satisfied than a created model based on linear regression maybe used practically.

## 4. Discussion of the research results

During the first stage of the research variables (i.e. stock prices of other companies, financial ratios, macroeconomic factors, sector indexes) which correlate with companies' stock prices $R \geq |0.95|$ are selected (Table 3).

During the research it was established that most of the companies' stock prices correlate with one or several variables: one variable (PZV1L, RSU1L, UTR1L, VLB1L); three variables (APG1L, LNA1L, TEO1L, LDJ1L); four variables (INV1L, SAB1L); five and more variables (PTR1L, CTS1L).

Table 3. Correlation analysis results

| Company | Variable | R ≥ \|0.95\| | Company | Variable | R ≥ \|0.95\| |
|---|---|---|---|---|---|
| PZV1L | SAB1L P/E | 0.9833 | TEO1L | LNA1L ROA<br>LNA1L ROE<br>TEO1L P/BV | –0.9583<br>–0.9531<br>0.9940 |
| RSU1L | INV1L P/BV | 0.9843 | LDJ1L | SAB1L<br>UTR1L P/E<br>VLP1L P/BV | 0.9753<br>0.9985<br>0.9576 |
| UTR1L | RSU1L EPS | –0.9515 | INV1L | UTR1L P/E<br>VBL1L EPS<br>VBL1L P/E<br>VBL1L ROA | –0.9977<br>–0.9949<br>0.9662<br>–0.9664 |
| VBL1L | APG1L EPS | 0.9531 | SAB1L | APG1L P/E<br>RSU1L P/E<br>UTR1L P/E<br>VLP1L P/BV | 0.9661<br>0.9573<br>0.9555<br>0.9700 |
| APG1L | LNA1L<br>PZV1L P/E<br>PZV1L P/BV | 0.9801<br>–0.9936<br>–0.9826 | PTR1L | APG1L P/E<br>LDJ1L ROA<br>LDJ1L ROE<br>PTR1L P/BV<br>RSU1L P/E<br>RSU1L P/BV<br>VLP1L GP<br>B2000GI<br>B8000GI | 0.9592<br>0.9865<br>0.9925<br>0.9978<br>0.9811<br>0.9842<br>0.9521<br>0.9869<br>0.9680 |
| LNA1L | LNA1L GP<br>PZV1L P/E<br>PZV1L P/BV | –0.9528<br>–0.9579<br>–0.9658 | CTS1L | PTR1L<br>LDJ1L ROA<br>LDJ1L ROE<br>PTR1L P/BV<br>PTR1L GP<br>RSU1L P/E<br>RSU1L P/BV<br>SAB1L P/E<br>B2000GI<br>B8000GI<br>E<br>I | 0.9758<br>0.9782<br>0.9604<br>0.9839<br>0.9641<br>0.9817<br>0.9863<br>–0.9893<br>0.9718<br>0.9682<br>–0.9538<br>–0.9764 |

VLP1L is the only company stock prices of which do not correlate with any variables. Due to this reason it is singled out for further analysis.

PTR1L and CTS1L are the companies' stock prices of which correlate with sector indexes, namely B2000GI Industrials and B8000GI Financials. Moreover, in the case of company CTS1L the stock prices correlate with macroeconomic variables such as import and export.

The research reveals that in the Lithuanian market environment the companies' stock prices correlate with their own financial ratio very rarely. It is more likely that they correlate with the financial ratios of other companies (Fig. 1).

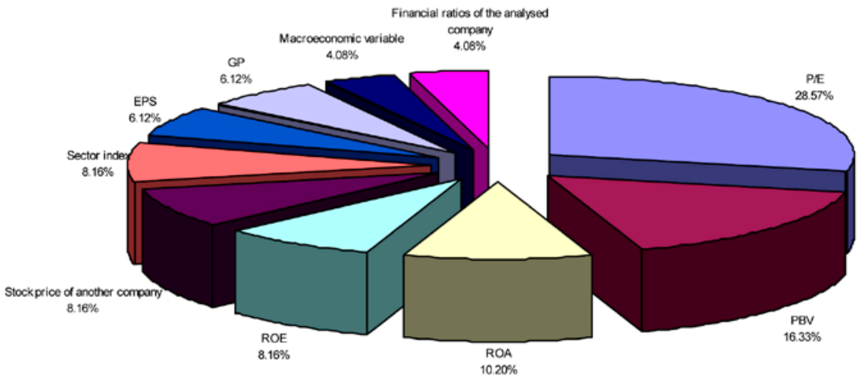


Fig. 1. Share (%) of the analysed variables correlating with companies' stock prices

P/E, P/BV, ROA and ROE are the most important financial ratios of the companies other than analyzed. The results exhibit both negative and positive correlations. Therefore, further research is necessary to clarify why these correlations exist. This will enable a deeper understanding of investment logics, and help in the developing of an improved stock price forecast model, which is detailed later on in this paper.

With reference to the findings presented in the Figure 1 regression analysis and ANOVA method are applied to equate the relationship between companies' stock prices and selected variables mentioned in the Table 1.

Essentially, companies' stock price forecast models for PZV1L, RSU1L, UTR1L, VLB1L can be supported by a linear regression when one variable is applied (2):

$$P_t = \alpha + \beta_1 x_1 + \varepsilon, \tag{2}$$

where: $\alpha$ and $\beta_1$ – linear regression coefficients; $\varepsilon$ – bias for the forecast value; $t$ – time period; Stock price forecast models for these companies are presented in the Table 4.

Table 4. Stock price forecast models with one variable

| Company | Stock price forecast model for the period 2010–2014 | General stock price forecast model |
|---|---|---|
| PTR1L | $1.2261 + 0.0398(SAB1L\ P/E) + \varepsilon$ | $\alpha + \beta(SAB1L\ P/E) + \varepsilon$ |
| RSU1L | $0.9673 + 0.4660(IVL1L\ P/BV) + \varepsilon$ | $\alpha + \beta(IVL1L\ P/BV) + \varepsilon$ |
| UTR1L | $0.5939 - 1.4455(RSU1L\ EPS) + \varepsilon$ | $\alpha + \beta(RSU1L\ EPS) + \varepsilon$ |
| VBL1L | $5.9058 + 42.5329(APG1L\ EPS) + \varepsilon$ | $\alpha + \beta(APG1L\ EPS) + \varepsilon$ |

Stock price forecast model supported by a linear regression with three variables is applied using equation (3):

$$P_t = \alpha + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \varepsilon, \tag{3}$$

where: $\alpha$ and $\beta_1$, $\beta_2$, $\beta_3$ – linear regression coefficients; $\varepsilon$ – bias for the forecast value; $t$ – time period.

However, stock price forecast models only for three companies i.e. APG1L, LNA1L, TEO1L are presented in Table 5.

Table 5. Stock price forecast models with three variables

| Company | Stock price forecast model for the period 2010–2014 |
|---|---|
| APG1L | $-2.0574 + 2.2581(LNA1L) - 0.0247(PZV1L\ P/E) + 1.8083(PZV1L\ P/BV) + \varepsilon$ |
| LNA1L | $1.2770 - 0.0884(LNA1L\ GP) - 0.0002(PZV1L\ P/E) - 0.1807(PZV1L\ P/BV) + \varepsilon$ |
| TEO1L | $0.4882 - 0.4924(LNA1L\ ROA) + 0.2076(LNA1L\ ROE) + 0.2269(TEO1L\ P/BV) + \varepsilon$ |
| Company | General stock price forecast model |
| APG1L | $\alpha + \beta_1(LNA1L) - \beta_2(PZV1L\ P/E) + \beta_3(PZV1L\ P/BV) + \varepsilon$ |
| LNA1L | $\alpha + \beta_1(LNA1L\ GP) + \beta_2(PZV1L\ P/E) + \beta_3(PZV1L\ P/BV) + \varepsilon$ |
| TEO1L | $\alpha + \beta_1(LNA1L\ ROA) + \beta_2(LNA1L\ ROE) + \beta_3(TEO1L\ P/BV) + \varepsilon$ |

During correlation analysis stage it appeared that stock prices of the LDJ1L company correlate with three variables. However, after regression analysis and application of the ANOVA method it was concluded that only one variable is significant i.e. UTR1L P/E (Table 6).

Table 6. Stock price forecast model for LDJ1L

| Company | Stock price forecast model for the period 2010–2014 |
|---|---|
| LDJ1L | $0.5832 + 0.0029(UTR1L\ P/E) + \varepsilon$ |
| Company | General stock price forecast model |
| LDJ1L | $\alpha + \beta_2(UTR1L\ P/E) + \varepsilon$ |

Meanwhile variables SAB1L and VLP1L P/BV are excluded.

Although stock prices of INV1L and SAB1L correlate with them, they should be excluded when equating the relationship between stock prices and variables for these companies. The results are presented in Table 7.

Table 7. Stock price forecast model for INV1L and SAB1L

| Company | Stock price forecast model for the period 2010–2014 |
|---|---|
| INV1L | $3.2887 - 0.0338(UTR1L\ P/E) + 0.0480(VBL1L\ P/E) + \varepsilon$ |
| SAB1L | $0.2344 + 0.023(UTR1L\ P/E) + \varepsilon$ |
| **Company** | **General stock price forecast model** |
| INV1L | $\alpha + \beta_1(UTR1L\ P/E) + \beta_3(VBL1L\ P/E) + \varepsilon$ |
| SAB1L | $\alpha + \beta_3(VBL1L\ P/E) + \varepsilon$ |

Similar to the LDJ1L case, unnecessary β coefficient values are eliminated together with the relevant variables. For the stock price forecast model linear regression with five and more variables is applied as follows:

$$P_t = \alpha + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_i x_i + \varepsilon, \tag{4}$$

where: $\alpha$ and $\beta_1$, $\beta_2$, ..., $\beta_i$ – linear regression coefficients; $\varepsilon$ – bias for the forecast value; $t$ – time period.

Although during correlation analysis phase it was concluded that stock prices of the companies PTR1L and CTS1L correlate with more than five variables, the application of the regression analysis and ANOVA method provides slightly different results as presented in the Table 8.

Table 8. Correlation and regression analysis results for the stock price forecast model when correlation analysis is misleading

| Company | Stock price forecast model for the period 2010–2014 |
|---|---|
| PTR1L | $-0.3154 + 0.1560(VLP1L\ GP) + 0.0009(B2000GI) + 0.0004(B8000GI) + \varepsilon$ |
| CTS1L | $3.45025 + 0.0005528(SAB1L\ P/E) + 0.0000001(B2000GI) -$<br>$0.0000001(B8000GI) + \varepsilon$ |
| **Company** | **General stock price forecast model** |
| PTR1L | $\alpha + \beta_7(VLP1L\ GP) + \beta_8(B2000GI) + \beta_9(B8000GI) + \varepsilon$ |
| CTS1L | $\alpha + \beta_{10}(SAB1L\ P/E) + \beta_{11}(B2000GI) - \beta_{12}(B8000GI) + \varepsilon$ |

It was established that stock prices of some companies, namely PTR1L and CTS11L, depend on sector indexes i.e. B2000GI (Industrials) and B8000GI (Financials). Due to this reason it is recommended to integrate additional variables i.e. EMA of different length (n days) into the stock price forecast model as presented in Table 9 to make more accurate stock price forecasts as it was determined during previous research (Table 9).

Table 9. Multiple EMAs to be used as additional variables to forecast stock prices of PTR1L and CTS1L

| B2000GI (Industrials) | Length (days) | Length (days) | Length (days) | Length (days) |
|---|---|---|---|---|
| Δ n-1 | 48 | 72 | 92 | 54 |
| N | 49 | 73 | 93 | 55 |
| Δ n+1 | 50 | 74 | 94 | 56 |
| B8000GI (Financials) | Length (days) | Length (days) | Length (days) | |
| Δ n-1 | 48 | 72 | 92 | |
| N | 49 | 73 | 93 | |
| Δ n+1 | 50 | 74 | 94 | |

When adding the variables into the stock price forecast model, three EMA lengths (for example, of 48, 49 and 50 days) should be used.

After the research in reference to historical data covering period 2010–2014 was conducted, it was concluded that a theoretical stock price forecast model for companies listed by Nasdaq OMX can be generated. Furthermore, such model can be improved in accordance with its practical application possibilities at the global level with reference to already developed international stock markets.

Based on the research results a general stock price forecast model is created (5):

$$P_{t+1} = \alpha + \beta_i P_i + \beta_k FR_k + \beta_m MF_m + \beta_n EMA(SI_n) + \varepsilon \,, \tag{5}$$

where: $\alpha$ and $\beta_i$, $\beta_k$, $\beta_m$, $\beta_n$ – linear regression coefficients; $P_i$ – $i$ – company's stock price; $FR_k$ – $k$ – financial ratios of the company under analysis or another company performing in the stock market; $MF_m$ – $m$ – macroeconomic factor; $EMA$ – EMA of $n$ days for the selected sector index; $SI_n$ – $n$ – sector index; $\varepsilon$ – bias for the forecast value.

To support the created stock price forecast model it is also useful to understand why the relationship between stock prices of particular companies and sector indexes exists.

In light of findings outlined above, there are all assumptions to carry out further research aimed at developing the created stock price forecast model at the global level, which will also enhance its practical application various stock markets.

## 5. Conclusions

This paper examined whether it is possible to create a stock price forecast model which integrates already known methods and models, namely fundamental and technical analyses, can be used practically by investors. With the reference to the companies listed by Nasdaq OMX Baltic, stock prices of 14 selected Lithuanian companies where analyzed, covering the period of 2010–2014 OMX.

The researched discovered a strong correlation ($R \geq |0.95|$) between stock prices and several variables, such as: stock prices of other companies than these under analysis; financial ratios (in most cases financial ratios of companies other than under review but also listed by Nasdaq OMX); macroeconomic factors; sector indexes.

It was established that stock prices of the majority of the companies examined correlate with one or several variables, among which P/E, P/BV, ROA and ROE are the generally held to be the most important financial ratios. In some cases the correlation between stock prices and the ratios is positive, while in other cases a negative correlation was found.

Other important variables include the stock price of companies other than analyzed, EPS and NPM ratios, country's import and export values as well as B2000GI (Industrials) and B8000GI (Financials) indexes.

For companies stock prices forecast models of which include sector indexes it is recommended to integrate an additional variables EMA of specific length (n days) selected particularly for these sectors. When adding the EMA, at least three different length (*n*-days) should be used to make stock forecasts more accurate.

However, application of the correlation analysis only is not reliable when creating a stock price forecast model because the selected variables may not be significant statistically and should be not integrated into the model. For these purposes the regression analysis and ANOVA method coupled with c-Squared Test results is recommended.

Potentially, the general stock price forecast model described in this paper can be applied practically to forecast stock prices in various. However, further research is needed in order to understand the drivers behind the relationship between stock prices of particular companies and sector indexes, financial ratios etc.

In light of findings outlined above, there are grounds for conducting further research towards developing stock price forecast model. All this will allow to drive and support growth of the economic and strengthen companies' growth perspectives.

In this case, for different stock markets the use of additional check measures is recommended. They include: Goodness of Fit Test (GFI); Tucker-Lewis Index (TLI); Normed Fit Index (NFI).

The stock price forecast model is suitable for application when the GFI, TLI or NFI value is close to 0.95.

Root Means Square Error Approximation (RMSEA) can be also used as an additional check measure for the created stock price forecast models. The stock price forecast model can be applied when RMSEA<0.95.

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