DO FINANCIAL INDICATORS, R&D AND CEO AFFECT THE AMERICAN AND EUROPEAN STOCK MARKETS?

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Abstract: Factors from economics, finance, technology and innovation areas are most likely to affect stock market prices, therefore, it is very important to investigate the potential risk factorsthat could affect these markets, using innovative method – artificial neural network (ANN). The main goal of this paper is to investigate the impact between corporate financial indicators, CEO compensation, R&D investment and stock marketand predict the trend of stock prices by these variables in USA and Europe. ANN provides a new way to optimize stock trading algorithms for an effective algorithmic trading strategy, involving different variables.Companies from Standard and Poor's 500 Index (SPX) and STOXX Europe 600 Index (SXXP)in total of 1100 were selected for the investigation, using Bloomberg professional terminal. Revenue, net income, sustainable growth rate, EBITDA, equity, short and long term debt, return on assets and on common equity, assets, liabilities and current liabilities, financial leverage, number of employees, gross and operating profit were selected as important financial indicators of companies. The annual time horizon was selected from 1999 to 2017 for the algorithm training of which 30% randomly has been assigned for the model testing and validation. The results of the investigation revealed that the financial results of companies uniquely influence the trend of prices in both stock markets. Financial leverage, EBITDA, sustainable growth rate, operating and gross profit as most significant financial factors, in particular, have a strong impact on both stock markets.However, CEO compensation and R&D investment have a more potent effect on USA stock market than on Europe’s stock market. Thus, if CEO compensation and R&D investment would increase in Europe, this stock marketwill have a strong growth potential. Otherwise, the SPX index price is six times higher than the SXXP index price and if CEO compensation and R&D investment will continue to grow in USA, while in Europe investment in innovation and financial incentives for top executives will stagnate, there is only a little chance that the European stock market will overtake to stock market of USA.

Keywords: Stock Markets, Financial Risk Factors, R&D Investments, CEO Compensation, Artificial Neural Network.

I. INTRODUCTION

Stock indices are reflecting the stock markets, because it displaysstock price trend of the largest company, so careful monitoring according to the stock indices and deep analysis by certain risk ratios of companycan help predict the stock market trend. The Standard and Poor's 500 Index (SPX) and STOXX Europe 600 Index (SXXP) are the most well-known stock indices among investors in USA and Europe. Both indices represents a different companies from USA and Europe.SPX index is a capitalization-weighted index of 500 stocks in USA. This index is designed to measure performance of the broad domestic economy through changes in the aggregate market value of 500 stocks representing all major industries. SXXP index represents large, mid and small capitalization companies across 17 countries of the European region.

The financial performance of companies affects the stock prices of these companies, so it is very important to identify the main financial indicators that make the most impact to trend of stock price of this company. According to the scientists, revenue, net income, sustainable growth rate, EBITDA, equity, short and long term debt, return on assets and on common equity, assets, liabilities and current liabilities, financial leverage, number of employees, gross and operating profit may be one of the most important risk factors for analysis. All authors agree that the financial results of the company affect the company's share price, however, there is a lack of detailed scientific articles that would examine the impact of R&D investment and CEO compensation on the company's stock price trend. R&D investments are defined as the company's own and borrowed funds redirecting to innovation. Innovation in an enterprise can include facilities, machines, production lines, computer programs or even improvements to the business chain through staff training. CEO compensation is defined as a high-level managerial salary, which additionally includes bonuses.

Therefore, the main goal of this paper is to investigate the impact between corporate financial indicators, CEO compensation, R&D investment and stock market and predict the trend of stock prices by these variables in USA and Europe. ANN provides a new way to optimize stock trading algorithms for an effective algorithmic trading strategy, involving different variables. Companies from Standard and Poor's 500 Index (SPX) and STOXX Europe 600 Index (SXXP) in total of 1100 were selected for the investigation, using Bloomberg professional terminal. The annual time horizon was selected from 1999 to 2017 for the algorithm training of which 30% randomly has been assigned for the model testing and validation.

II. PRIOR LITERATURE

Stock indices, purchase and sales signals, various traditional and innovative forecasting methods are analyzed in scientific articles. The empirical part and the data of the author of each scientific article are different, but the purpose of all of them is similar - more effective decision-making for investors.

According to the authors Ivanova and Wille (2002) a moving average technique can be used for analysing the stock indices dynamics. The authors say that two moving averages with different time horizons are especially important. Also it is very important to distribute the maximum and minimum in the moving average signal. The dynamics of stock prices is influenced by economic and political factors. Any economic news affects the movement of stock prices. It should be emphasized that any negative economic news affects the fall in stock indices. Especially prices fell during all global economic crises. According to the authors Vamvakaris et al. (2018) have investigated that all of the major economic crises that have taken place over the past twenty years around the world have greatly affected the behaviour of stock price indices. They say that each global economic crisis has affected stock indices differently, however can predict future trends carefully analysing the stock index market using horizontal visibility graph. Analyzing the stock index market it is important to consider systemic risk. According to the authors Li et al. (2018) in high-volatility financial environments systemic risk can be detected using network topology. The authors in their study proposed to apply the minimum spanning tree with the upper tail. Papaioannou et al. (2017) offers a ’’Buy and Hold‘‘ trading strategy for analysing price of stock indices. The strategy is based on the most liquid futures deals from the four major asset classes: equities, bonds, commodities and foreign exchanges. Authors use S&P500 stock index data and prove that such a strategy can be one of the successful alternatives for predicting future trends. In order to predict stock index price trend can be used the density forecast. According to the authors Hua and Zhang (2008) this forecast is „an estimate of the probability distribution of the possible future values of a random variable’’ and are increasingly being used. They propose a GARCH model with two-piece normal distribution. Authors Rivera and Arroyo (2012) use histogram time series (HTS) and interval time series (ITS) to analyse S&P500 stock index price trends. However according to the authors Aubert and Grudnitski (2014) „the relationship between the market mispricing of pro forma earnings announcements and the degree to which pro forma earnings are quantitatively reconciled with GAAP (Generally Accepted Accounting Principles) earnings’’ are more important than other risk factors of market. They proved it using Euro Stoxx index data. Ozturk and Richard (2015) use stochastic volatility leverage models to assess stock indices price trends according S&P500 data. These authors Michaelidess et al. (2016) note that it is very important to analyze stock indices during crises, to anticipate future crises, and to try to forecast share prices through them. They suggest using innovative techniques artificial neural networks. These authors Brida et al. (2016) also examine stock price indices in pre-crisis and post-crisis periods using Euro Stoxx index data. They use ,,symbolization methods to the raw data to study the behaviour of the market structure in different, normal and critical, situations’’. Liu (2009) analyzed the stock index Nikkei 225 and came to the conclusion that ,,when stocks are added to (deleted from) an index, more (less) information should be generated and incorporated into their prices, leading to higher (lower) pricing efficiency and lower (higher) return predictability for them.’’ This author has applied runs test. According to the authors Danbolt et al. (2017) stock market index FTSE 100 is different from that of the Amercan or other country’s stock indices as companies may fall into this index according to ear rules that are based on market capitalization. A technical analysis can be used to assess the stock index price trend (Ilalan, 2016). One of the most significant technical analysis indicators is the Elliott wave principle. According to the Ilalan (2016) it is very important to find a linkage between Elliott wave principle and fractional Brownian motion. This author used the stock index Nikkei 225 and proved that the technical analysis could predict trends of stock prices. For the evaluation of the stock index price trend, it is also possible to use the autoregressive conditional jump intensity (ARJI) model (Lee et al., 2007). These authors used CME-Nikkei 225 and SIMEX-Nikkei 225 data. It is necessary to anticipate market volatility in order to predict the prices of stock indices, and this is rather complicated. Authors Becker et al. (2006) in their study show that the VIX index can be used to assess the volatility of the stock market, but it is not the best option. The financial results of the company are also very important in order to assess the stock price trend. According to financial data, enterprises can be divided into stable, reliable and unstable, unreliable. According to the authors Linares-Mustaros et al. (2018) companies can be classified by evaluating these financial indicators: fixed assets, inventory, quick assets, equity, long term debt, short term debt, current assets, current liabilities, total assets, sales and profit. Authors Algabaa and Boudta (2017) of the stock market forecast also assess the financial indicators of companies such as returns on assets, risky assets, risky equity, equity premium, short term equity premium, long term equity premium, price earnings ratio, price to book ratio, price earnings to growth ratio and bond equity yield. According to the authors Dong et al. (2018) in order to identify corporate risk, it is possible to analyze financial indicators such as total liabilities, market value of total assets, current liabilities, book value of total assets, working capital, sales, market equity, net income and market value of total assets. ''Stock market price is one of the most important indicators of a country's economic growt. That's why determining the exact movements of stock market price is considerably regarded'' (Gocken et al., 2016). Movement of stock market indexes can be investigated through statistical approaches and by employing machine learning techniques. The statistical approach of models with linear models like weighted moving averages, autoregressive integrated moving average (ARIMA) and autoregressive moving average (ARMA) haven't been very accurate because of non-linearity in the financial markets (Guégan, 2009).While machine learning methods were gaining popularity in recent years. Researchers successfully used methods like K-Nearest Neighbors (KNN) (Chen et al., 2017), Decision Tree (DT) (Nair et al., 2010), Artificial Neural Network (ANN) () and Support Vector Machines (SVM) (Yu et al., 2014).

SVM and ANN were used by Kara et al. (2010) with ten technical indicators and provided comparable results showing that financial indicators are feasible features that can predict stock price movement direction. According to Gocken et al. (2016) hybrid Artificial Neural Network (ANN) model can be used for prediction stock market. This model could include ''in exploiting capabilities of Harmony Search (HS) and Genetic Algorithm (GA)''. Also Moghaddama et al. (2016) predicts stock index using artificial neural network. In their investigation the ability of ANN in forecasting the daily NASDAQ stock exchange rate was analysed (Moghaddama et al., 2016). ''Several feed forward ANNs that were trained by the back propagation algorithm have been assessed'' (Moghaddama et al., 2016). The methodology used in this study considered the short-term historical stock prices as well as the day of week as inputs and daily stock exchange rates of NASDAQ from January 28, 2015 to18 June, 2015 are used to develop a robust model (Moghaddama et al., 2016).

A single stock index was more analyzed in scientific articles. One or two methods have also been applied by scientists. Stock index prices and price trends were the basis. However, the global stock indexes view is composed of stock indexes less analyzed. The methods proposed by researchers can be applied to analyzing several key stock indices in order to make more effective investment decisions.

METHODOLOGY

1.1 Dataset

Investigated dataset was collected by using Bloomberg terminal. Stocks were selected from two indexes: from USA – Standard and Poor's 500 Index (SPX) and from Europe – STOXX Europe 600 Index (SXXP). For each stock we have extracted yearly financial reports from 1999 to 2017 and combined them with the closing price of the day when the annual financial statement was published.

Collected data contained these features from annual financial statement: R&D expense, total compensation paid to CEO, revenue, net income, sustainable growth rate, EBITDA, total equity, short term debt, long term debt, return on assets, return on common equity, total assets, total current liabilities, total liabilities, financial leverage, number of employees, gross profit, operating margin and stock price.

As for classification tasks machine learning algorithms requires target label the new parameter of the stock price movement was introduced. Each data point was assigned to either "good investment" class or "bad investment" class. These classes were calculated by comparing closing stock price during the publishing day of annual financial statement with the closing price of the stock after three years. Those companies which experienced continuous 10% growth for a three years were considered as a good investment and all remaining ones were treated as bad investments. As it was needed to know the exact stock price after three years from financial report date dataset was filtered to contain only entries where this calculation was possible.

Also data entries without information about yearly R&D expenses and CEO compensation were removed as it made it possible to investigate impact of those features to the stock price movement prediction performance. Therefore models with and without those features were prepared for comparison during classification phase. All features were normalized so the higher input values wouldn't overwhelm smaller ones.

Finally data points from S&P500 and EURO STOXX were kept separated and haven't been mixed into one model. This was done to be able to evaluate and compare USA and Europe stock markets independently.

1.2 Classification methods

Non-linear machine learning algorithms were selected to compute binary classification task. Both ANN and SVM showed good results in previous research (Wen et al. 2010, Ticknor et al. 2013).

Artificial Neural Network

Artificial neural networks (ANNs) are based on biological example of a central nervous system and are used to compute functions that depends on large number of variables. These networks consists of "neurons" which values are transferred from input layer through hidden layer into output nodes. The learning procedure follows by passing inputs and setting weights among the layers and neurons. Weights acts as a memory and trained networks can work with new data points.

Single hidden layer fully connected feedforward ANN was constructed in order to solve stock movement prediction task. The architecture of ANN consisted of three layers and is illustrated in Figure 1. Inputs of neural network were features from yearly financial statements. R&D expenses and CEO compensation features were omitted or included in some models so the input layer consisted of 17, 18 or 19 neurons depending on which features were investigated. The number of neurons in the hidden layer was picked by optimizing ANN hyper parameters. The output of constructed neural network was a class pattern of either 1 or 0 which have demonstrated the computed growth or drop of the stock price after three years. Therefore the output layer had only one neuron for representation of "good" or "bad" investment.

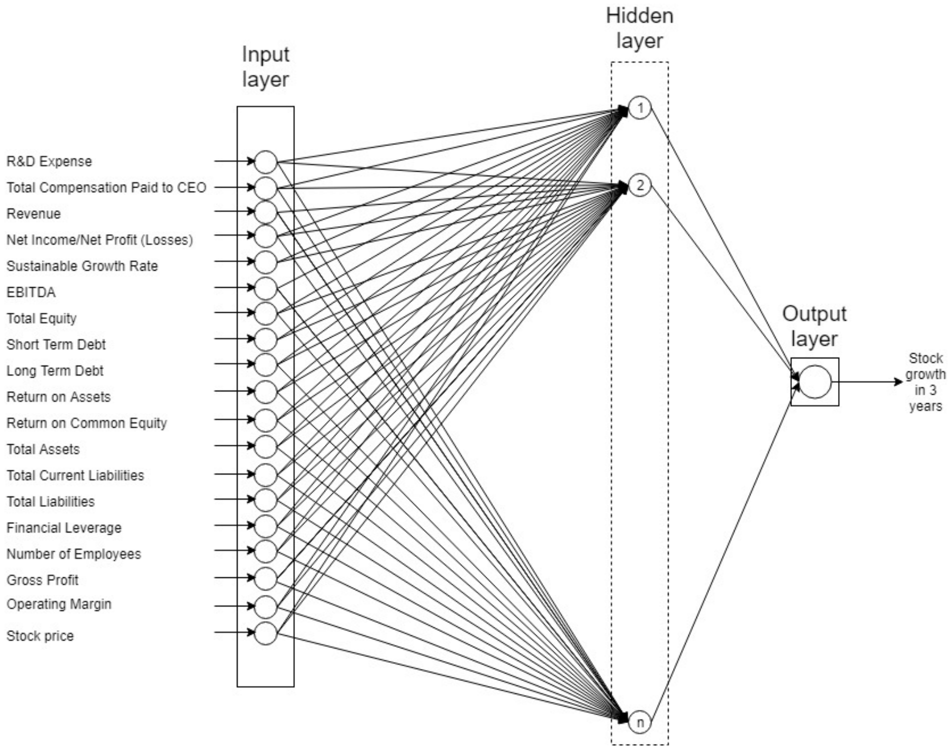

Figure 1 Feedforward single hidden layer ANN for stock growth classification

SVM

Support Vector Machine can be used to solve classification and regression tasks. In case of binary classification SVM generates a hyperplane in higher-dimensional feature space to separate two data classes. The main goal of SVM is to find a hyperplane which has optimal (maximum) margin between it and data samples (Yu et al., 2014). Data points that donates the position of this hyperplane are called support vectors. Hyperplane can be calculated by (1) equation:

$$h(\vec{x}) = \vec{w}^T\vec{x} + \omega_0$$

(1)

where W is weights vector and ω_0 is a distance from the origin to the hyperplane.

The result of a hyperplane for feature vector $\vec{x}$ is $h(\vec{x}) \geq 1$, when $\forall\vec{x} \in class\ 1$ and $h(\vec{x}) \leq -1$, when $\forall\vec{x} \in class\ 2$. SVM task is to find a hyperplane which has maximum margin between two classes. This is done by minimizing weights vector $\vec{w}$. Following Karush-Kuhn-Tucker conditions and using Langrange multipliers λ (Shigeo, 2010) we can describe this nonlinear optimization task as dual problem (2):

$$\begin{cases} \max L(\lambda) = \sum_{i=1}^{N}\lambda_i - \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N} y_i y_j \lambda_i \lambda_j K(x_i, x_j) \\ \sum_{i=1}^{N}\lambda_i y_i = 0 \\ C \geq \lambda_i \geq 0, \forall i = 1, \dots, N \end{cases}$$

(2)

The SVM kernel function can be described in multiple ways but most commonly used is Radial Basis Function (RBF) kernel which is defined as (3):

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

(3)

RESULTS

ANN and SVM models were trained using 70% of data using eight prepared datasets with varying feature sets (4 variants) and 2 stock indexes. Separate models were constructed to investigate differences between USA and Europe stock markets. Moreover for each market four models were trained in order to amount the impact of R&D expense and CEO compensation features: without them, including both of them, including R&D expenses and including CEO compensation. Remaining 30% of data were used for result validation and evaluation.

Accuracy, precision and F1-score were computed to evaluate the performance of proposed models. The number of True Positives (TP), True Negatives (TN), False Positive (FP) and False Negatives (FN) from confusion matrix were tracked in order to calculate these values. Performance parameters are defined in (4)-(7) equations:

$$Recall = \frac{TP}{TP + FN} \quad (4)$$

$$Precision = \frac{TP}{TP + FP} \quad (5)$$

$$F1score = 2\frac{Precision \cdot Recall}{Precision + Recall} \quad (6)$$

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \quad (7)$$

The classification results of USA stock market S&P500 index showed that the greatest accuracy of 72.2% was achieved by using ANN with data model that contained all features including R&D expense and CEO compensation while SVM demonstrated 64.1% accuracy on the same data. Removal of these features from the data model impacted both ANN and SVM by lowering accuracy to 69.2% and 62.9% respectively. Evaluation parameters from all trained models for USA stock market can be found on Table 1. Separate inclusion of only R&D expenses or CEO compensation feature still gave better results compared to the model without them although CEO compensation is a stronger feature of them. But the best results were achieved with both of these features.

	ANN			SVM		
	Accuracy	Precision	F1score	Accuracy	Precision	F1score
Base S&P500 features	0.692	0.622	0.754	0.629	0.622	0.754
Including R&D expenses and CEO compensation	**0.722**	**0.732**	**0.766**	0.641	0.645	0.743
Including CEO compensation	0.72	0.727	0.766	0.628	0.627	0.745
Including R&D expenses	0.71	0.721	0.756	0.623	0.619	0.75

Table 1 Classification results of S&P500 stock index by ANN and SVM

Europe STOXX classification results demonstrated that inclusion of R&D expense and CEO compensation didn’t make any impact neither to ANN nor to SVM with 70.1% and 70.2% accuracy respectively. Looking at the full evaluation of EURO STOXX classification results in Table 2it can be seen that additional features only increases complexity of the model without giving a boost to the performance. Therefore CEO compensation and R&D expenses variables should be dropped from the EURO STOXX model.

	ANN			SVM		
	Accuracy	Precision	F1score	Accuracy	Precision	F1score
Base EURO STOXX features	0.701	**0.761**	0.646	0.702	0.66	**0.721**
Including R&D expenses and CEO compensation	0.701	0.688	0.696	0.702	0.663	0.718
Including CEO compensation	**0.707**	0.771	0.645	0.696	0.656	0.713
Including R&D expenses	0.707	0.694	0.701	0.696	0.653	0.717

Table 2 Classification results of EURO STOXX by ANN and SVM

Differences in terms of R&D expenses and CEO compensation impact to the long-term stock prices movement in USA and Europe stock indexes can be investigated by comparing results of the constructed models. It can be said that the R&D investment and CEO compensation culture is much stronger in USA compared to Europe counterpart and creates greater influence to long-term stock growth. While these parameters in Europe companies only added additional noise to the prediction model.

CONCLUDING REMARKS

The financial indicators of the companies (R&D investment, CEO compensation, revenue, net income, sustainable growth rate, EBITDA, total equity, short term debt, long term debt, return on assets, return on common equity, total assets, total current liabilities, total liabilities, financial leverage, number of employees, gross profit and operating margin) uniquely affected the stock market in the short and long term. Finally, these financial indicators can be divided into four main groups under the influence of equity markets: indicators that have a positive impact in the short term, indicators that have a negative impact in the short term, indicators that have a positive impact in the long-term and indicators that have a negative impact in the long-term.

The results published by companies on increased revenue, net income, gross profit and operating margin had a positive impact on stock prices in the short term, both in USA and in Europe. The company's announcement of the results of an increased short term debt, long term debt, total current liabilities, total liabilities and financial leverage had a negative impact on stock prices in the short term, both in USA and in Europe. A negative return on common equity and assets negatively affected the stock price trend in the long term, both in USA and in Europe. And the most important thing is that R&D investments and CEO compensation have had a greater positive effect on stock price growth in the long term in USA than in Europe.Strategic sustainable investment in innovation in USA companies was significantly higher than in European companies. Salaries and bonuses for assuming risks to managers in USA companies were significantly higher than in European companies as well. There was also the risk that information in European companies was not fully disclosed about all investments in innovation and salaries and bonuses received. R&D investment and CEO compensation together with other traditional financial indicators can be a great measure in assessing the company's stock price trend, stock reliability and risk in the long term.

Hence, if CEO compensation and R&D investment would increase in Europe, this stock market will have a strong growth potential. Otherwise, the SPX index price is six times higher than the SXXP index price and if CEO compensation and R&D investment will continue to grow in USA, while in Europe investment in innovation and financial incentives for top executives will stagnate, there is only a little chance that the European stock market will overtake to stock market of USA.

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