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Procedia Economics and Finance 30 (2015) 22 – 29

Procedia Economics and Finance

www.elsevier.com/locate/procedia

3rd Economics & Finance Conference, Rome, Italy, April 14-17, 2015 and 4th Economics & Finance Conference, London, UK, August 25-28, 2015

Selecting Macroeconomic Influencers on Stock Markets by Using Feature Selection Algorithms

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Abstract

Many studies in finance literature aims to find which macro-economic factors influence stock markets and by doing so to predict market returns. There hasn't been a common approach to find a mutual explanation about relationships between factors and stock markets. Results differ according to advantages- disadvantages of methods used on different markets. We tried to decide which factors has influence on predicting the movements of stock markets. We used sequential forward selection algorithm on Turkish stock market: Borsa Istanbul, and picked interest rate, exchange rate, industry production index, oil price, gold price as candidate indicators (including one and two month lagged values of each) along with stock market's one and two period lagged index values. Our results show that, one month lagged stock market indicator index values are enough to predict market indicator index's future values.

Peer-review under responsibility of IISES-International Institute for Social and Economics Sciences.

Keywords: Stock Markets; Prediction; Macroeconomic Factors; Neural Networks; Feature Selection

1. Introduction

There are plenty of studies in finance literature which aims to explain effects of macro-economic factors on stock markets and so to predict returns. By using different –but mostly statistical- methodologies and features, these studies were not able to find a mutual explanation about relationships between factors and stock markets. Results differ according to advantages- disadvantages of methods used on different markets: Single or multi factor models, ARCH models, vector auto regression model, Johansen co-integration test, Granger causality test, variance decomposition method, artificial neural networks, support vector machines are examples.

Researchers add the macro-economic indicator they think important to their models. This will cause misinterpretation of model outputs if not related factors are included. So, factor selection is another important component for the success of analyze, together with method used. Frequently used factors includes GDP, industry

Peer-review under responsibility of IISES-International Institute for Social and Economics Sciences.
doi:10.1016/S2212-5671(15)01251-4

production index, unemployment rate and savings as general economic situation indicators; treasury bill returns, debt instruments, monetary policies of central banks, discount rates and LIBOR as interest rate and monetary policy indicators; inflation rate, oil and gold prices as price level indicators and exchange rates and foreign money reserves as international fund moving indicators. There have been lots more factors used by several studies.

Our study aims to decide which indicator(s) has influence on predicting the movements of Turkish stock market by using sequential forward selection algorithm. Interest rate, exchange rate, industry production index, oil price, gold price are our candidate indicators (including one and two month lagged values of each) along with stock market's one and two period lagged index values.

The most popular and used method in predicting returns of stock markets is Capital Asset Pricing Model (CAPM). Introduced by Markowitz (1952) to select optimal portfolio; the model is improved by Sharpe (1964), Lintner (1969), Mossin (1966) and used in both theory and application. Convenience of model is due to its simplicity because it only uses market factor as determinant of market index movement. This causes ignorance of many factors that will affect the market.

In order to observe effects of macro-economic factor changes on asset returns, Arbitrage Pricing Theory (APT) will be used as a multi factor model. It is developed by Roll and Ross (1980) and in their study, Chen, Roll and Ross (1986) found consistent results with APM. In his study, Buyuksalvarci (2010) analyzed influence of several factors on Borsa Istanbul -100 (BIST100) based on APM. He found interest rate, industry production index, oil price, exchange rate and money supply as determinants of movement. Chen, Roll and Ross (1986) found that difference between long and short term interest rates, expected and unexpected inflation, industry production and the spread between high and low level bonds are significantly priced in market. Oil price was not a determinant for market. Kwon, Shin and Bacon (1997), said the significant factors are dividend yield, foreign exchange rate, oil price and money supply on Korean stock market. Oil price gets more attention in these kinds of studies after the collapse of eastern bloc. In their study about the sensitivity of Australian industry equity returns to an oil price factor, Faff and Brailsford (1999) found pervasiveness of this factor beyond Australian market under some degree and found significant oil price sensitivity in several industries. Hondroyiannis and Papapetrou (2001) also indicated that oil prices have negative influence on market in Greece. Kapusuzoglu (2011) investigated oil price influence on BIST100, BIST50 and BIST30 indexes with Johansen co-integration test and found long term relationship between oil prices and indexes.

In their study on developing country markets, Bilson, Brailsford and Hooper (2001) found exchange rate as most significant variable on market returns in 12 out of 20 countries. World market index was second significant variable after exchange rate. Their study indicates the improving effect of financial liberalization and capital flows over countries. Sayilgan and Süslü (2011) analyzed several country stock market returns (including Turkey) with panel data analysis and found that while exchange rate, inflation rate and S&P500 index affect returns, interest rate, GDP, money supply and oil prices were not affecting. Fedorova and Pankratov (2010) remarked the importance of oil price and exchange rate factors on Russian MICEX index. Exchange rate factor solitarily analyzed in Turkish market by Aydemir and Demirhan (2009) and found correlative relations between BIST100, service, finance, industry and technology indexes.

In Rapach, Wohar and Rangvid (2005)'s study, within 12 industrialized countries, interest rate became most significant factor to explain stock market returns. Alam and Uddin (2009) also analyzed interest rate effect on stock markets of several countries and found significant. Tangjitprom (2012) stated that interest rate is the only factor significant in Thailand market.

Even in same country, different market indexes may have different relations with same factors. For example, Hess (2003) analyzed Swish market and found that industry specific indexes have different sensibilities to variables; industries which depends on import reacts external shocks while others do not. Another example for industry differentiation will be of Maysami, Lee and Hamzah (2005)'s on Singapore market. Only Singapore stock market index and real estate index have significant relationships with all macro-economic variables and other indexes reacts industry specific variables only. Humpe and Macmillan (2009), Suvanujasiri, Boriboon and Ahmadi (2010), Pal and Mittal (2011), Kalra (2012) also stated macro-economic factors are significant in explaining market returns.

Accurate forecasting methods are crucial for portfolio management in financial institutions. Ultimate goal of all these mentioned studies is about to understand where the stock market is moving towards. As said before, models used and selected features have influence that can't be ignored on performance of prediction. Studies performed by Preminger and Franck (2007), Hamzaçebi, Akay and Kutay (2009), Hyup Roh (2007), Zhu et al. (2008), Celik and Karatepe (2007), Ghiassi, Saidane and Zimbra (2005), Khashei and Bijari (2010), Niaki and Hoseinzade (2013), Leung, Daouk and Chen (2000) with artificial neural networks and all concluded ANNs can be used effectively for forecasting. Guresen, Kayakutlu and Daim (2011) found that ANN model outperforms other two model they used by little difference. In their study, Kara, Acar Boyacioglu and Baykan (2011) compared ANN and support vector machine methods to predict the direction of movement in Istanbul Stock Exchange (ISE) National 100 Index and found average performance of ANN is more than SVM. Just like them, Olson and Mossman (2003) also found neural network outperforms the best regression alternatives in forecasting. It can be said that every method comes with its own pros and cons.

But which factors has to be included in analysis? To answer this, feature selection will be used as an algorithm that can remove the redundant and irrelevant factors, and figure out the most significant subset of factors to build the analysis model. He, Fataliyev and Wang (2013) used principal component analysis, genetic algorithms, and sequential forward search in order to find out which indicators are most important. They said principal component analysis is the most reliable one (but not with large data dimensions) but others are also useful. We used Sequential Forward Selection method with a neural network in our study.

Neural Networks and Learning Methods

In this work, in order to predict the indicator index, neural network is used. As stated in Haykin (1999), how brain accomplishes a particular task or a function, neural network is machine which is designed to model that task or function like brain. There are two learning methods to design the neural network. These are supervised and unsupervised learning methods. Supervised and unsupervised learning methods can be described as learning with a teacher and without a teacher, respectively. In this study supervised learning method is used as seen in the figure below. Teacher serves the desired response to the system and learning system is adjusted according to error between the teacher and output of the learning system. In this study performance function of the network is selected as mean squared normalized error performance function. That is, performance of the neural network is calculated with mean squared errors.

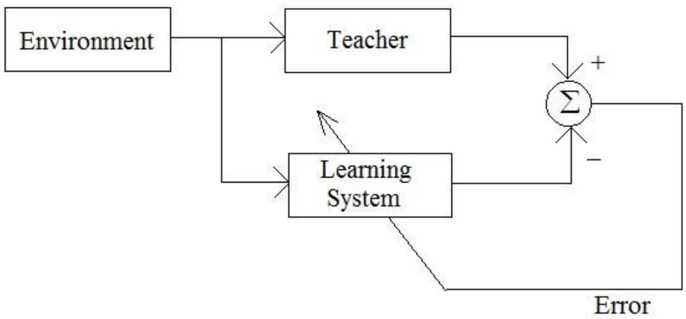

Fig. 1. Supervised neural network.

Multilayer perceptron (MLP) is a neural network type which is widely used and in this study also MLP type neural network is used. It consists of three parts that are named as input layer, hidden layer, and output layer. MLP can be seen in Figure 2. MLP solve the problem by using the error back-propagation algorithm. There are two passes in error back-propagation algorithm. These are forward pass and backward pass. In the forward pass, effect of applying the input vector to sensory nodes propagates from a layer to another layer. Then output for this input vector is obtained. In the backward pass, weights of the network is adjusted according to the error-correction rule Haykin (1999). As stated in above error is obtained from the difference between the output of teacher (desired response) and learning system.

Back-propagation is used with some learning and training function parameters. In this study, back-propagation learning function is selected as gradient descent with momentum weight and bias learning function. And back-propagation training function is selected as gradient descent with adaptive learning rate back propagation. These types of functions are selected as trial-and-error method because the success of these parameters on the neural network performance depends on the data structure and it changes from a data set to another data set.

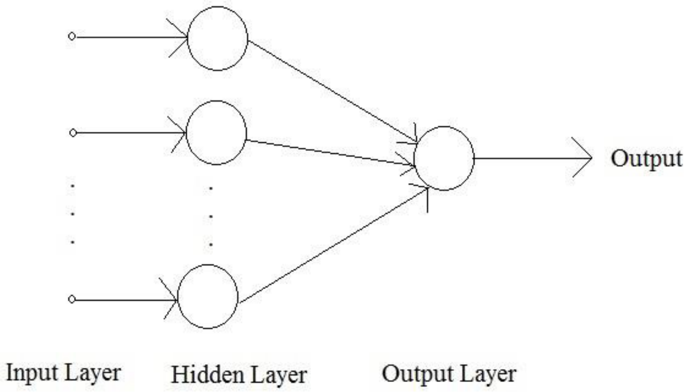

Fig. 2. Example of a MLP.

In order to train the neural network, data set is divided two parts, train and test data set. Train data set is used to train the neural network and test data is used to test the performance of neural network. How test or train data are selected from overall data set changes according to the type of learning method. In this study, K-fold cross validation learning method is used.

2. Learning Method

Data set is divided as train and test data according to K-fold cross validation learning method.

Data is divided K parts as stated in Figure 3. For each experiment one part is used as test data and K-1 parts are used as train data. By this way all the samples in the data set are used as both train and test data.

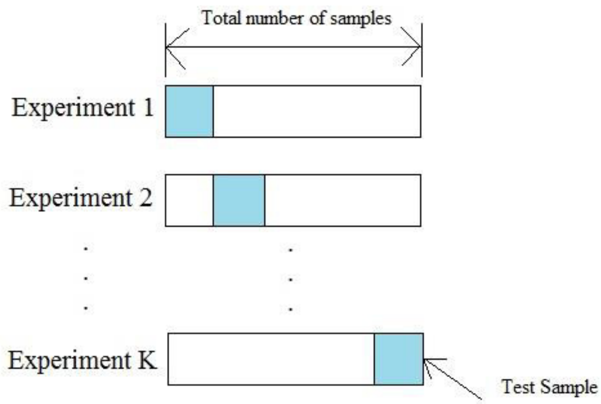

Fig. 3. K-Fold Cross Validation.

Because of dimensional differences, all feature and target sets are normalized to [-1, 1] interval. After learning and testing, errors are calculated with de-normalized values. Errors are percentage values of differences between actual index values and predicted values generated by neural network to actual index values.

3. Feature Selection

In this study, 17 features are used to predict the indicator index. However, all of the features sometimes do not increase the prediction performance and contrarily some features may exist in the data sets that decrease the performance. Secondly, the smaller numbers of features, the faster computation speed of prediction. As stated in Kudo and Sklansky (2000), large numbers of features include garbage features and studying with large number of data causes both time consuming computation and decreasing the performance of analysis. Therefore in order to decrease the number of features by removing the garbage features and increase the performance of prediction by this way, a feature selection algorithm is used. Feature selection is a method to select useful features from a large number of feature set in order to obtain efficient and better solution to a given problem (Muni, Pal and Das, 2006). In literature, feature selection method is categorized in three groups according to their search method. These are exponential, sequential and stochastic methods (Marcano-Cedeño, Quintanilla-Domínguez, Cortina-Januchs and Andina, 2010). In literature, Marcano-Cedeño et al. (2010), Marcano-Cedeño et al., Wang, Yang and Chung (2006), Wang, Yang and Chung, Jain and Zongker (1997), Mineichi Kudo and Sklansky (2000), Liwicki and Bunke (2007), Muni, Nikhil and Jyotirmay (2006), Biskin, Kuntalp and Kuntalp (2010), Schenk, Kaiser and Rigoll (2009) show that feature selection algorithms increase the performance of classification or prediction.

In this work, a sequential feature selection method which is called as Sequential Forward Selection (SFS) is used. SFS is widely used because it is a very easy and fast algorithm (Marcano-Cedeño, Quintanilla-Domínguez, Cortina-Januchs and Andina, 2010). Therefore, in this work, SFS algorithm is used as a feature selection method because of its speed and simplicity in order to decrease the number of features and increase the prediction performance.

4. Sequential Forward Selection Method

SFS is a bottom-up search method. At the first step, SFS algorithm starts with empty data set. After that, this subset is grown by adding new features into this data set. At each iteration, if a feature increases the objective function more than other features when using together with the features in subset, then it is added to this subset. That is, only one feature is added to the subset at each iteration. SFS algorithm is given in below. X and W represent feature set and selected feature subset, respectively. Subindex of X and W denote the iteration number, like and . Objective function, which corresponds to prediction performance, represented as J(W).

1st Step: n=1: $W_n = \{\varnothing\}$ *and* $X_n = \{x_1, x_2, \ldots x_N\}$

2nd Step: Chose the best feature, $\{x_k\}$, which increases the objective function more than other features in X_n in case using with previously selected features in the W_n, $J\left(W_n \bigcup \{x_k\}\right)$. Then our new feature subset is expanded by adding $\{x_k\}$ to the presented subset, $W_{n+1} = W_n + \{x_k\}$ and x_k is removed from the feature set *X*. Then now, the new feature set is $X_{n+1} = X_n \setminus \{x_k\}$

Iteration number is $n = n+1$

If it does not exist a feature $\{x_k\}$ which increases the objective function, then SFS algorithm goes to the 4th step. Iteration will stop and also algorithm will not continue anymore.

3rd Step: Repeat the 2nd step.

4th Step: Stop the iteration.

When the SFS algorithm ends, features in the *W* set are presented to neural network.

5. Determining Epoch Number

Epoch number is determined by trial and error. Without an optimized number of epoch, success of prediction of model decreases. If epoch number is lower than appropriate one, network cannot be trained enough. On the other hand, if a higher epoch number is used, network will be over trained. In both situations, performance indicator of success decreases.

In order to find optimal epoch number for model, we run simulations including all features with epoch numbers of 150, 300, 450, 600, 750, 900, 1050, 1200, 1350, 1500, 1650, 1900. Epoch Number with lowest error rate was 1500.

6. Candidate Features

Our candidate features are consisted of 17 macro-economic factors including their one and two period lagged values plus stock market index's one and two period lagged values. BIST100 index is regarded as market indicator in financial studies and analyses.

Table 1: Factors as Candidate Features

Exchange Rate	Interest Rate	Industry Production Index	Inflation Rate	Oil Price	BIST100 (-1)
Exchange Rate (-1)	Interest Rate (-1)	Industry Production Index (-1)	Inflation Rate (-1)	Oil Price (-1)	BIST100 (-2)
Exchange Rate (-2)	Interest Rate (-2)	Industry Production Index (-2)	Inflation Rate (-2)	Oil Price (-2)	

Every factor thought to be a representative of different economic dimensions which considered as influencers on a country's stock market. We tried to remove insignificant factors and decrease percentage of error in predicting stock market movements for simplicity and efficiency.

Our data set includes monthly values of mentioned factors and market index between dates 01/2003 and 02/2014.

7. Analysis Results and Conclusion

Neural network was trained with candidate features in order to predict BIST 100 index's value. With all 17 features, prediction error was 10.13%. To decrease simulation run time and increase success rate, SFS algorithm used. SFS algorithm selects features which improves efficiency of model when used together and creates a new feature data set. BIST100 index's one period before value (BIST100(-1)) is the only feature included. Prediction error was decreased to 9.6%. All other features cause a decrease in success. Although quantitatively not significant, prediction realization has done with a very small data set.

Results show that, one month lagged index values are enough to predict market indicator index's forthcoming value without including other factors. This situation will be associated to the property of index to reflect information about actual economic conditions. Existing information that thought to be carried by economic factors are already included in index value. Thus, financial decision makers, investors and risk analysts can work much more efficiently without dealing with large amount of data, troubling with collecting and storing costs and completing analysis in a in a short span of time.

Future works will include other factors considered in prediction studies in literature and examine a larger feature pool to find if performance and success of analysis increase by selecting more features as inputs.

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