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# Comparison of Prediction Performances of Artificial Neural Network (ANN) and Vector Autoregressive (VAR) Models by Using the Macroeconomic Variables of Gold Prices, Borsa Istanbul (BIST) 100 Index and US Dollar-Turkish Lira (USD/TRY) Exchange Rates

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## Abstract

Artificial neural network (ANN) approach, the application of artificial intelligence, which has been improved by the simulation of cognitive learning process of human brain, has been commonly used in recent years. In this study, the relationship between the exchange rate of US Dollar-Turkish Lira (USD/TRY), gold prices and the Borsa Istanbul (BIST) 100 index has been estimated by using the ANN method and the method of Vector Autoregressive (VAR). The ANN method has been applied by means of multi-layered feedforward neural networks (MLFNs) by using monthly data over the period of January, 2000 and September, 2014. VAR method has also been applied with the same variables for the same period of time. In this study, different from the studies conducted up to present, ENCOG machine learning framework has been used along with JAVA programming language in order to constitute the ANN. The training of network has been done by resilient propagation method. The results obtained by the ANN method have been compared with the results obtained by the econometric forecasting method of VAR. Our results indicate that the ANN approach has superior performance of prediction capability than the VAR method.

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*Keywords:* VAR Model; Artificial Neural Network; Forecasting; Multi-layered Feedforward Neural Networks; Financial Crisis; JAVA.

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## 1. Introduction

Since the Great Depression in 1929, the world economy has experienced several financial crises that had grievous impacts on both industrialized and developing countries. These major periods of high financial stress and crises include

: the Tequila crisis in 1994 in Mexico, the 1984 savings and loans (S&L) crisis in the US (Zheng, 2013, p. 2), the Asian financial crisis in 1997 and 1998, the Russian financial crisis in 1998, the financial crisis in Brazil in 1999, the financial crises in 1994 and 2001 in Turkey and the financial crisis in Argentina in 2001. All of these mentioned crises have some common features such as financial liberalization, weak financial and banking systems that are open to fraud, unsustainable macroeconomic policies such as high trade deficits and undisciplined budget policies and finally, global economic conditions and political instability.

With the emergence of the 2008 global financial crisis, researchers accelerated their empirical works on prediction of financial crises and developing early warning systems. Due to systemic risk and the contagion effect of the recent crisis, economists and policymakers realized how devastating consequences can adverse financial shocks cause on the real economy. In this context, one of the most important negative impacts of the recent crisis has been the substantial increase in the rate of unemployment. Although the severity of this problem varies significantly from one country to another, young people and women have been badly hit all around the world.

The major purpose of this study is to predict stock market crash and financial distress before financial crisis by using different macroeconomic variables such as exchange rate of US Dollar-Turkish Lira (USD/TRY), gold prices and the Borsa Istanbul (BIST) 100 index. Our specific objectives in this study are identifying (if any), the causal relationship between these variables and predicting a potential stock market crash or a financial crisis by using these variables in order to minimize their costs to the economy.

This paper is composed of four sections including introduction. The second section examines the main empirical literature which employs either the Artificial Neural Network (ANN) method or the Vector Autoregressive (VAR) method to test the relationships between different variables to predict financial distress or stock market crashes before they occur. The third section explains the empirical methodology used in the study and presents empirical findings with their interpretations. The fourth section is the conclusion part.

## 2. Literature Review

In the last few decades, ANNs have been frequently used to solve complicated problems and to test the relationship between different variables. Empirical researches clearly indicate that they can be used as efficient tools to analyze critical issues in business decisions. In this context, ANNs may help to solve problems in finance as well as in other fields with poorly defined models. Neural networks have been useful to predict volatile financial variables, which are quite difficult to guess with classical statistical and econometric methods such as exchange rate and stock market

Many researchers prefer to utilize ANN to conduct their studies in different fields. However, only limited number of researchers prefer to use ANN in their empirical researches to identify financial distress, to develop early warning systems or to predict financial crisis. In one of these studies, Nag and Mitra (1999, p. 184) utilized the ANNs to develop an early warning system to detect exchange rate crisis for Indonesia, Malaysia and Thailand in the time period of 1980 and 1998. They employed sixteen different variables for their research and compared their results with the results obtained by the signal approach. They conclude that the ANN model has a superior performance of prediction as compared to the signal approach.

Frank and Schmied (2003, p. 2) used the ANN model in the prediction of speculative attacks in Russia and Brazil in 1998 and 1999. They observed that trying to determine the nonlinear relationships by using linear models weakens the possibility of the prediction of financial crises. However, they assert that by using ANNs in their study, they obtained a more accurate performance as compared to the logit models in the prediction of speculative attacks.

Fioramanti (2008, p. 150) tried to predict the debt crisis in less developed countries by using the data that belong to the period of 1980 and 2004 by utilizing the ANN model. He argues that the ANN model can obtain more accurate results as compared to other early warning systems thanks to its high flexibility and its ability to analyze the nonlinear relationships. In his study, he employed yearly data of 46 developing countries that belong to 34 independent variables. Similar to the findings of Nag and Mitra (1999, p. 183) and Franck and Schmied (2003, p. 1), Fioramanti (2008, p. 149) observed that the ANN model provided more accurate and successful results.

Ban and Mazibas (2009, p. 28) developed neural network models to classify failed and non-failed banks prior to their failure. When they conduct their study, they used the financial and operational ratios of 36 selected banks operating in Turkey as an input to the two types of neural network structures which are Multilayer Perception (MLP) and Generalized Feed Forward Networks (GFNs). In addition to the ANN models, they used discriminant and logistic regression models to compare their classification performances. Their results reveal that the ANN outperforms other models.

VAR model can be used to determine the relationships between different variables, which might be useful to predict stock market crashes or financial crises. It is also one of the most successful and flexible models for the analysis of multivariate time series, which has been made popular by the famous macroeconometrician Christopher Sims (1980) in order to model causal relations and joint dynamics among a variety of macroeconomic variables. Other major researchers, who have made significant contributions to the empirical literature concerning modeling time series with VAR include Hamilton (1994), Campbell, Lo and MacKinlay (1997) and Mills (1999).

Dhokal, Kandil and Sharma (1993, p. 54) are among the researchers, who prefer to use VAR model to test the relationships between stock prices and macroeconomic factors. Reside and Gochoco-Bautista (1999, p. 461) and Fujii (2002, p. 2) studied the relationship between exchange rates. Daly (2003, p. 75) identified the relationships among the stock markets. Phylaktis and Ravazzola (2005, p. 1031) tested the interaction between the exchange rate and the stock market. Chen (2003, p. 40) identified the relationship between money supply (M1) and stock price by utilizing a VAR model for Granger causality test. All these studies have a common point that they use similar methodology to analyze the relationship among the macroeconomic variables. They utilize either VAR or Vector Error Correction (VEC) model, to model the variables to identify short-term or long-term relationship among these variables.

Koc and Akgul (2013, p. 42) aimed to present structural regime change periods of Turkish economy over the period of 1990 and 2007. They, in their research, utilized Markov Switching Autoregressive (MS-VAR) models to determine these regime structures. They conducted their analysis by using various macroeconomic variables such as current account, Gross Domestic Product (GDP) growth rate, ratio of import coverage by export and interest rate series for the period of 1992 and 2007. By determining three different regimes in this period, their study contributed positively to reduce uncertainty and to assist in decision making process in money and financial markets.

Zhou and Zhang (2014, p. 135), in their study, tried to predict stock market crash before financial crises with the aim of mitigating potential losses. They decided to select Granger causality test and VAR model to be used in their research to test the time lag. The sample period for their study is between 1987 and 2013. They employed the macroeconomic variables of exchange rate, Hong Kong Interbank Offer Rate (HIBOR), money in circulation and T-Bill rate to conduct their studies. By using VAR Lag Order Selection Criteria, they found that they can use one or two month forward HIBOR to predict stock market crash in Hong Kong index in the future.

### 3. Methodology and Findings

#### 3.1. VAR models

VAR model is an easy to use model for the analysis of multivariate time series. It has proven to be especially useful for describing the dynamic behavior of economic and financial time series and for forecasting. With VAR models, it is possible to approximate the actual process by arbitrarily choosing lagged variables. Thereby, one can form economic variables into a time series model without an explicit theoretical idea of dynamic relations. The most easy multivariate time series model is the bivariate VAR model with two dependent variables,  $y_{1,t}$  and  $y_{2,t}$ , where  $t = 1, \dots, T$ . The development of the series should be explained by the common past of these variables. That means, the explanatory variables in the simplest model are  $y_{1,t-1}$  and  $y_{2,t-1}$ . The VAR(1) with lagged values for every variable is determined by;

$$y_{1,t} = \alpha_{11}y_{1,t-1} + \alpha_{12}y_{2,t-1} + \varepsilon_{1,t}$$

$$y_{2,t} = \alpha_{21}y_{1,t-1} + \alpha_{22}y_{2,t-1} + \varepsilon_{2,t}$$

The error terms  $\varepsilon_{it} \sim iid(0, \sigma_{\varepsilon_i}^2)$  are assumed to be white noise processes, which may be contemporaneously correlated, but are uncorrelated with any past or future disturbances (Hacker and Hatemi, 2008, p. 605).

VAR analysis assumes that all the stochastic processes in the autoregressive system are variance-covariance stationary. If this condition is not met, little confidence can be placed in the VAR regression results. Since most, if not all of the data here are highly autocorrelated and tend to drift over time, some form of detrending is obviously required before the models can be estimated. Our choice was influenced in part by the recent work of Dickey and Fuller (1979, p. 430). The Augmented Dickey Fuller (ADF) test results from VAR model are shown in Table 1.

We decide to use monthly data of three variables, which are the exchange rate of USD/TRY (USD), BIST 100 index (BIST) and gold prices (GP) over the time period of 2000 and 2014 to build our model. An important preliminary step in model building and impulse response analysis is the selection of the VAR lag order. In this study, we use some commonly used lag-order selection criteria to choose the lag order, such as the Akaike Information Criteria (AIC), the Hannan-Quinn Criterion (HQC), the Schwarz Information Criterion (SIC) and the Final Prediction Error (FPE). Based on AIC and FPE, the lag order we have chosen is 2. Because the data we used are monthly data, the result is reasonable. Based on SIC and HQC, we will try the models with lag orders, which are equal to 11 or 2 as well.

Table 1 shows the results of the unit root tests with the 5% Mackinnon critical values. The table indicates that all the variables are non-stationary, specifically, the variables are I(1).

Table 1 : ADF stationary Test Results

Variables	Level Value			First Difference			
	None	Intercept	Trend and Intercept	None	Intercept	Trend and Intercept	
USD	1.0078(0) 0.9172(pvalue)	-2.0151(0) 0.2802(pvalue)	-2.7693(0) 0.2107(pvalue)	-9.22638(0) 0.000(pvalue)	-9.3790(0) 0.000(pvalue)	-9.357046(0) 0.000(pvalue)	
BIST	1.5502(0) 0.9702(pvalue)	0.0584(0) 0.9616(pvalue)	-3.0669(1) 0.1176(pvalue)	-11.1903(0)* 0.000(pvalue)	-11.3511(0) 0.000(pvalue)	-11.3634(0) 0.000(pvalue)	
GP	1.3376(1) 0.9543	0.3920(1) 0.9066(pvalue)	-2.0456(1) 0.5719	-9.9681(0)* 0.000	-10.2438(0) 0.000	-10.2221(0) 0.000	

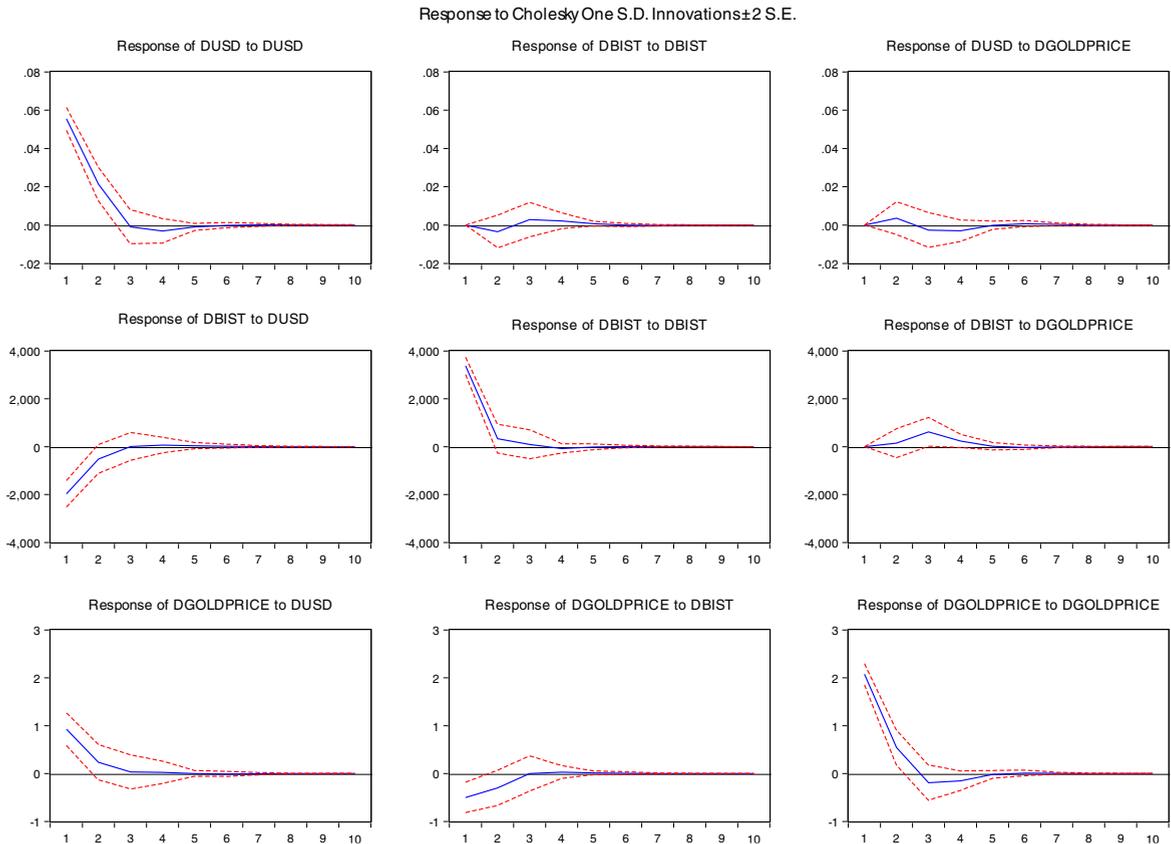


Fig. 1. The Results of Impulse Response Analysis With VAR Model

The impulse response analysis quantifies the reaction of every single variable on an exogenous shock to our model. The impulse response function of VAR is to analyze dynamic effects of the system when the model receives the impulse. As many researchers, we also study impulse responses in structural VAR models based on identifying assumptions about the short-run and long-run responses of the economy to individual structural shocks (e.g., Shapiro and Watson 1988; Blanchard and Quah 1989). In our VAR model, we have three variables, which are the exchange rate of USD/TRY (USD), BIST 100 index (BIST) and gold prices (GOLDPRICE). From Figure 1, we can see that when the impulse is BIST, every response of goldprice is positive at each time of the response period. Almost half responses of USD is positive and the value fluctuates around the line zero. On the other hand, every response of BIST is mostly negative.

### 3.2. Artificial Neural Network (ANN)

In this paper, the data of 177 months between January 2000 and September 2014, which were obtained from the Electronic Data Distribution System of the Central Bank of the Republic of Turkey (CBRT) and the website of the World Bank, were used. In the empirical analysis part, three different variables, which are USD/TRY exchange rates (USD), gold prices (GP), BIST 100 index (BIST) were used. In the prediction of the next 36 months of crisis indicator data in Turkey, we prefer to use feed-forward, backpropagation, multi-layered ANN. It consists of an input layer, two hidden layers, and an output layer as shown in Figure 2. The independent variables represent the input vector and each value is provided to the network in one of these input layer nodes, where each node consequently represents an explanatory variable. The desired output is determined as the value of the output layer nodes. In other words, regardless

of the total number of layers, each node is linked to all nodes in the previous and in the following layers. Obtained models have been investigated whether the data will show a decrease or increase in comparison with previous or latter month.

In this study, in terms of applied method, a feed-forward and multilayered ANN has been used which is composed of  $3 \times 12 = 36$  inputs, 3 outputs and 2 hidden layers in which 25 neurons are included in each layer. In the layers of the network, the sigmoid activation function has been used. In addition to this, the resilient propagation learning algorithm has been used for the learning of the network. In this learning process, the error value of 0.1 % has been determined as a target value, which provides a limit between the desired values. In Figure 2, a three-layer network structure, artificial neurons and inter-layer relations have been demonstrated schematically.

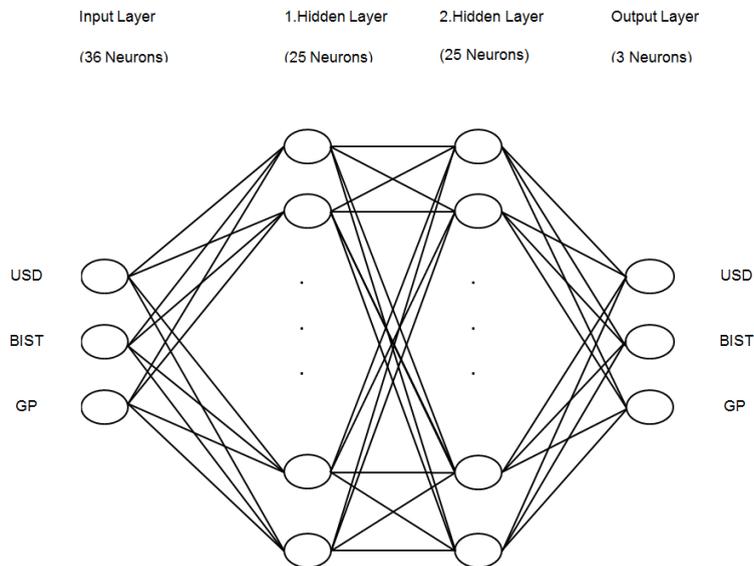


Fig. 2. A Brief Multilayered Feedforward Neural Network (MLFN) Architecture of the Proposed Methodology for ANN

Because of ease of use, time series, which take part in ENCOG framework, have been given preference in the Temporal Neural Dataset class of software, which constitute the data sets. The normalization and the denormalization of data have been done with the help of built-in functions found in framework. While the network is being trained, the twelve-month lagged values of data were given as prologue and forecasting of the 37th month has been demanded. In the same manner, we try to estimate starting from the 37th month of 176 months that are in the data set. For each month to be predicted, ANN has been trained iteratively with its previous three-year data. For the 178th and the following months, again its previous three-year data has been given to the ANN as training set, and the missing months have been filled by the prediction values obtained in previous iterations. In other words, different networks have been used in our analysis in the calculation of each prediction value as compared to other studies which use a single network.

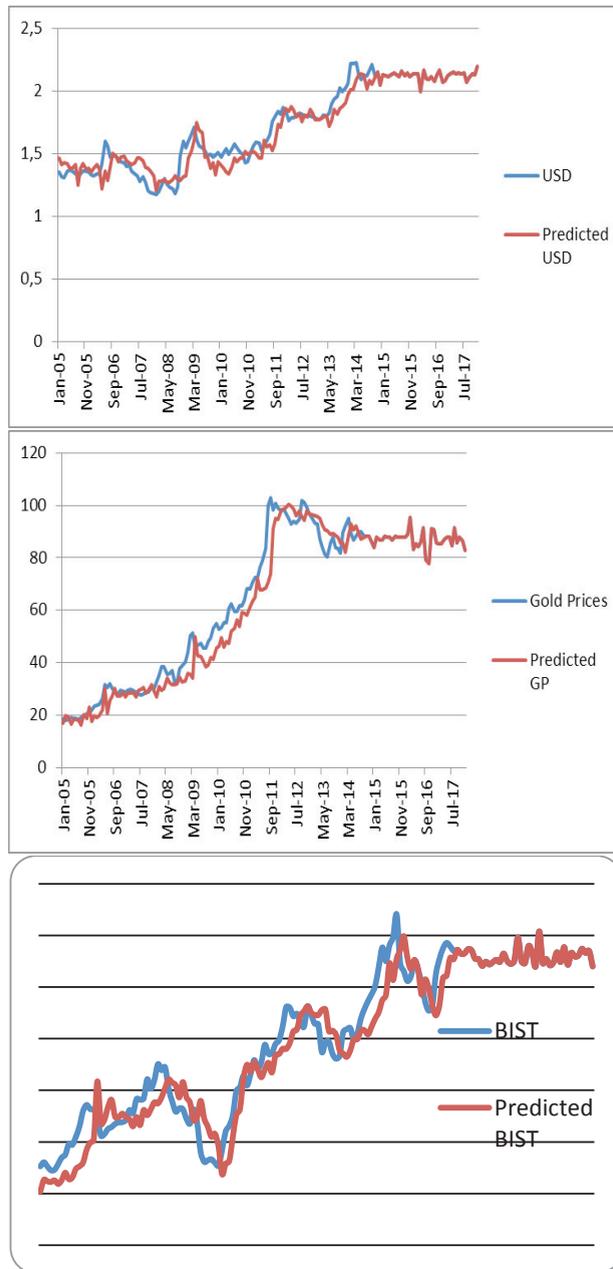
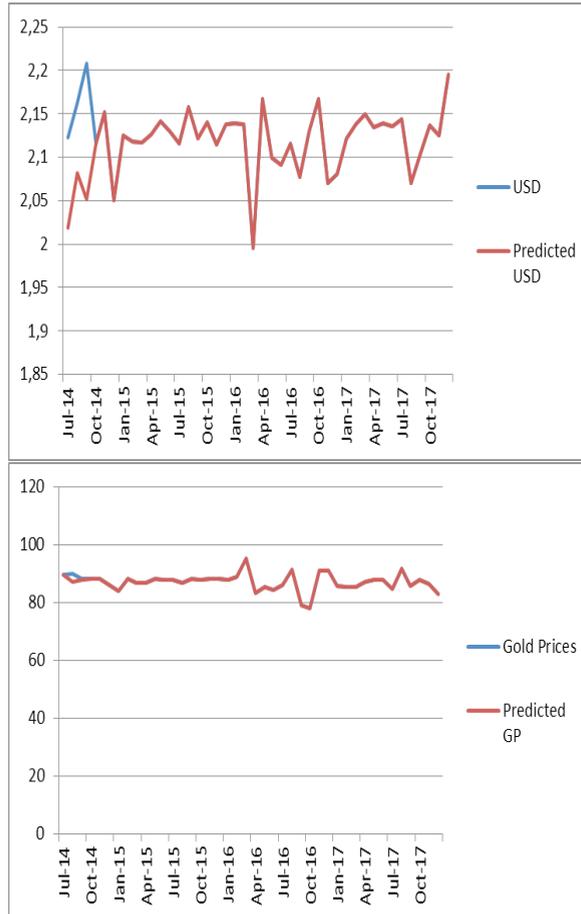


Fig. 3. Comparison of Real And Predicted Values With ANN

Figure 3 plots the relationship between the real and predicted values for each month during 2005 and 2017. It can be seen from figure that the real and the predicted values are very close to each other. We can see the impact of the recent global financial crisis on Turkish economy from the figure clearly by analyzing its effects on these three variables.

Turkish economy also experienced the financial crises of 1994 and 2001 until 2008. The period of 2002 and 2007 was a stability period thanks to structural reforms applied in Turkish economy, and the positive course of events in the

global economy. However, this stability period came to an end with the 2008 financial crisis. As it can be seen from Figure 3, as a result of the recent crisis, the exchange rate of USD/TRY (USD) has risen considerably since 2008. Gold price (GP) also climbed up sharply starting from 2008 till 2012. This trend indicates that gold prices actually rose because investors were in search of safety especially at the outset of the crisis. As the risk perceptions of investors decreased, gold prices also declined. BIST 100 index (BIST) dropped substantially in 2008, but bounced back and entered into an increase trend. On the other hand, these trends were interrupted and the BIST 100 index (BIST) dropped significantly in 2011 and 2014 similar to the situation in 2008.



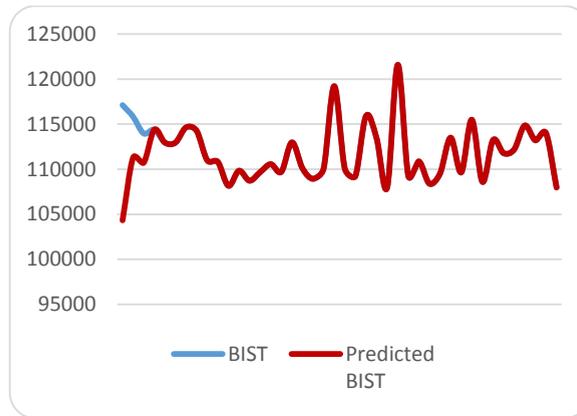


Fig. 4. The Future Values Predicted with ANN

Figure 4 presents the future values of three macroeconomic variables obtained from the ANN. Except for gold prices, both the exchange rate of USD/TRY (USD) and the BIST 100 index (BIST) fluctuate significantly during the prediction period of 2015 and 2017. Gold prices (GP) enter into a stable period except for April and October, 2016. On the other hand, when the exchange rate of USD/TRY (USD) drops sharply in April and October 2016, the BIST 100 index (BIST) skyrockets, which indicates that these two variables are actually reversely correlated. When the data are interpreted in detail and previously experienced crises in Turkish economy are taken into consideration, it is recommended that investors should note these dates carefully. Furthermore, there is a probability of a financial distress or a financial crisis starting from October 2017. Consequently, there may be significant amount of capital outflows and investors may demand higher risk premiums to compensate for their possible losses during this period.

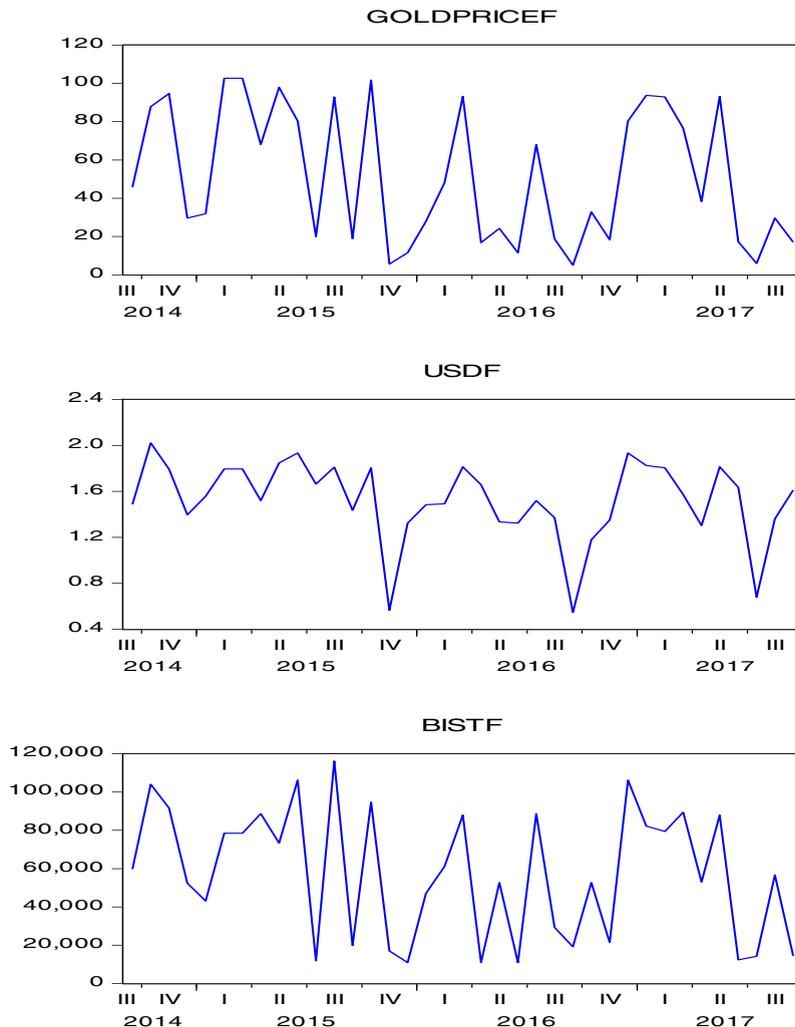


Fig. 5. The Future Values Predicted With VAR Model

Figure 5 demonstrates the future values predicted with VAR model. When it is examined in detail, it is seen clearly that the USD/TRY exchange rates (USD), BIST 100 index (BIST) and gold prices (GP) will decrease sharply during the fourth quarter of the 2015 and the third quarter of the 2016 and 2017. Interestingly, all of these three variables fluctuate significantly and these predictions do not correspond to ANN results. On the other hand, according to the VAR model, given dates can be evaluated as the crisis signal for the Turkish economy.

**4. Conclusion**

The current financial crisis, the dynamism of financial markets, and the globalization process have accelerated the obsolescence of financial crisis prediction models and emphasized the need to reformulate these models. Neural networks arise as a powerful tool to enhance modelling flexibility and dynamism and to identify the most outstanding properties to predict financial crisis.

In this study, the causal relationship between macroeconomic variables such as gold prices (GP), the exchange rate of USD/TRY (USD) and the BIST 100 index (BIST) has been investigated. We aimed to predict potential stock market crashes or financial crises in order to minimize their costs to the economy. We used two different methods of Artificial Neural Networks (ANNs) and the Vector Autoregressive (VAR) method to conduct this study. According to the findings of the ANN method, there is a possibility of significant fluctuations for the USD/TRY exchange rate (USD) and the BIST 100 index (BIST) during the time period of 2015 and 2017 except for gold prices (GP). Strikingly, our findings based on the ANN method reveal that there is a possibility of a financial distress or a financial crisis starting from October, 2017.

According to the results of VAR method, all of the three variables fluctuate significantly between 2015 and 2017. Our research reveals that the results of VAR method is different than our results obtained with the ANN method. In this regard, it can be said that ANN method generates better estimations and more accurate results than the VAR method. Some of the major literature, which support our findings include Nag and Mitra (1999, p. 183), Franck and Schmied (2003, p. 2), Fioramanti (2008, p. 151) and Ban and Mazibas (2009, p. 50).

We suggest that researchers can obtain more accurate results and make more precise predictions by using more macroeconomic variables. This study can also be extended to a larger time period covering the major crises experienced in 1990s to see the prediction capabilities of different methods such as VAR, ANN or other alternative methods. By extending this study with more variables and more countries covering a larger time interval, a potential global crisis can even be predicted prior to its occurrence.

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