ESTIMATING THE NON-PERFORMING LOANS IN DEVELOPMENT AND INVESTMENT BANKS BY NEUTRAL NETWORKS NARX MODELS

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ABSTRACT

Considering the main function of the banks, which can be defined as the credit deployment, it can be easily stated that one of the most important performance measure is the ratio of non-performing loans over total loans. Although deterministic models like time series, linear regression and panel data analysis are widely used, the literature utilizing artificial neural network is relatively narrow. The capacity of neural networks for predicting non-performing loans is not well known by the Turkish banking sector especially by the investment and development banks. In this paper, one of the most important intelligent techniques called Nonlinear Autoregressive Network with Exogenous Inputs (NARX) is applied to a dataset of Turkish development and investment banks in order to estimate non-performing loan ratio. The study shows that the prediction performance of the NARX model can be considered as satisfactory; however the performance of prediction strongly depends on the bank characteristics and the variable choice itself.

Keywords*: Non-Performing Loans, Artificial Neural Network, Development and Investment Banks*
Jel Classification*: C45, G21, E51*

ÖZET

KALKINMA VE YATIRIM BANKALARI TAKİBE DÖNÜŞEN ALACAKLARININ YAPAY SİNİR AĞLARI (YSA) – NARX MODELİ KULLANARAK TAHMİN EDİLMESİ

Kredi faaliyetlerinin bankacılığın ana fonksiyonu olduğu gözönüne alındığında, bankalar açısından en önemli performans ölçütlerinden birinin tahsili gecikmiş alacakların toplam alacaklara oranı olduğu rahatlıkla söylenebilir. Her ne kadar determnistik modeller olan, zaman serileri, panel data analizleri ve doğrusal regresyon modelleri çok fazla kullanılmış olsa da, yapay sinir ağlarından faydalanan çalışmalar oldukça azdır. Yapay sinir ağlarının tahmin kapasitesi bankacılık sektörü tarafından özellikle de yatırım ve kalkınma bankaları tarafından çok da bilinmemektedir. Bu çalışmada, çok önemli bir yapay sinir ağı tahmin modeli olan Dış Değişkenl Doğrusal Olmayan Otoregresif Ağ

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Modeli (NARX) kalkınma ve yatırım bankalarına, takibe dönüşen alacakoranını tahmin etmek amacıyla uygulanmıştır. Bu araştırma; sözkonusu YSA modelinin iyi bir tahminci olduğunu göstermiş ancak tahmin performansının banka tipine ve bağımlı very cinsine gore değiştiğini göstermiştir.

Anahtar Kelimeler: *Tahsil Gecikmiş Alacaklar, Yapay Sinir Ağları, Kalkınma ve Yatırım Bankaları*
Jel Sınıflanması*: C45, G21, E51*

Introduction

Banks are organizations, which penetrate all activities in economy and almost in contact with all members in market with different levels. They can be considered as a channel through which not only the financial sources but also the best and the promising financial and economical applications are carried. Because of that close interaction between banks and other parties, any problem in banking sector is also felt very strongly by all other players in the market very quickly. Due to such strong and active interaction between different players as investors, customers and public organizations with banks; banks themselves are defined as the trigger points in many crises all over the World (Ozcan at all 2013). As the main function of the banks is the money transfer through the credit channel, the performance of the credit management is the heart of the banking industry. Credit deployment and management performance can be also measured with the non-performing loans or non-performing loan ratio which is defined as the non-perfoming loan / total loan (Louzis et al, 2012; Klein, 2013). As this ratio is a performance measurement for the credit activities, such ratio could be a determinant as a poor management practices, expanded risk taking, inadequate credit deployment procedures, pervasive internal control system, decreased company performance in whole economy or in one more concentrated sector in which the bank is active itself (Miletic & Miletic, 2015; Alan et al, 2000).). The last economic crisis has pointed out that the credit risk would contribute to all other different kinds of risks. It is closely connected with market and operational risks. It is not only a disease but also a prognosis for other diseases. It is such a risk that in middle or long term, it might cause the liquidity crisis, which is the basic reason for the banks to be defaulted. It might be a sign for the operational problems as well as inefficient internal procedures. Credit activities with poor performance might be a very important indicator not only for the current problems but also for the forthcoming crisis as well. Besides information about the market, it might also supply warning points related to bank itself like the deteriorated internal processes, loose control systems in credit management. Due to those reasons indicated above, it is extremely important to understand and make research about that variable. Moreover, such ratio for banks itself, can be used as the early warning for current or future strategic plans as well as for the short term tactical moves. In addition, for the regulatory body and central banks, monitoring of such ratio would be used for the controlling and supporting whole economy over the banking industry.

In this paper the non-performing loan ratio in the Turkish development and investment-banking sector is analyzed. Such research is important because it is pointing out an important issue in specific banking sector in Turkey. Moreover, it is the first time in Turkey that such research is done with this methodology.

Turkey is locally and globally one of the most important actors in world economy because of its GDP (15^{th} largest in 2015) and membership of the global organizations (OECD, ISEDAC, EU Candidate). The Turkish banking sector is growing very fast and it takes attractions of many investors. However, according to the international researchers, it is also considered as one of the most promising sectors, which doesn't take the attention that it deserves (Eichengreen, 2002).

Development and investment banks can't accept the personal or corporate savings. Because of that, they have to use the international or more structural and institutional funds that have more stipulations on the deployment. Such stipulations would affect both strategies and the policies of banks resulted in more limited short term and long-term activities. These banks generally support more fruitful and promising investment activities in politically important sectors or fields, which are strategically supported by government.

In Turkey, such banks are operating with more capital, which causes higher capital adequacy ratio (CAR). Although it seems like the efficiency of such banks are low, according to the recent research they are as efficient as the others (Karahanoglu, 2015).

Most of the researchers are concentrated on other well-known financial ratios like CAR and profit based ratios. Non-performing loan ratio as well as non-performing loan itself did not get the attention that it deserves. However, it is one of the most important factors, which indicate the banks profit. Any expected or unexpected loss coming from the defaulted credit must be compensated from the banks' profit as well as capital. When the non-performing loan ratio increases, for the stock market, it is also accepted as the negative sign for the banks' performance. Monitoring of such ratio is vital for the banks as such ratio would affect not only their internal process and profits but also their market share value and long-term liquidity problems.

Regulatory and the policy-making institutions in an economy would use the non-performing loan ratio as an indicator of more severe cases like crisis. So, estimating or monitoring such ratio would give advantage to those institutions to get the necessary precautions to support the systemically important organizations or banks in advance to prevent the more defective developments.

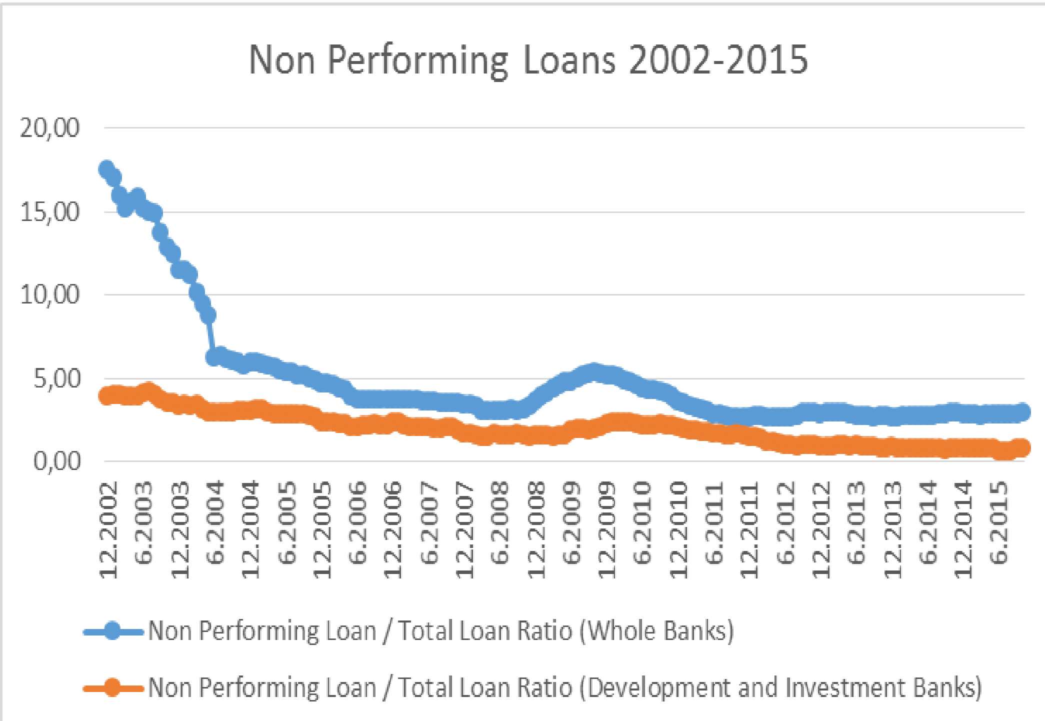
As indicated before, the purpose of this study is to estimate the non-performing loans ratio in development and investment banks in Turkey by Artificial Neural Networks. By following the previous researchers, the 9 other financial ratios and 6 main macroeconomic variables are used. Data was divided into training/validation and test set. The data, which is used for this study, includes 11 banks and their quarterly financial ratios between 2003 March-2015 September as well the other macroeconomic variables for the same period. For each bank different ANN models were applied and the best one is chosen according to the MSE and R values, error performance measured with SML and error autocorrelation. The outcomes of the models were presented for each bank and interesting results were reached based upon the bank ownership structure.

Turkish Banking Sector and Non-Performing Loans

Following the local 2001 crisis in Turkey the non-performing loans have reached %20 percentage at the end of 2002. Just after then, it starts declining very strongly to almost %3 due to new economic conditions as well as the strong government's solid financial plans. However in 2009, again because of the global economic crisis, it has reached the value over %5, which is a relative increase of %60 in 2 years. Such an increase was again followed by the sharp decrease in following years of 2010 and 2011. Since then, it shows a more stable value around %3 as it is seen in the graph below.

Compared with the whole banking sector, the non-performing loan ratio is lower for development and investment banks. It follows the same pattern with commercial banks but the volatility as well as the ratio is much lower. The reason for this is based upon two main characteristics for such banks. The first one is that such banks have very strong internal systems, which is audited by the main commercial fund suppliers. Second one is that the biggest development and investment bank in Turkish banking sectors are the public organizations, which would avoid the predatory lending (predatory lending is a stress coming from profit making and asset value increase).

Graph I: Turkish Banking Sector Non- Performing Loan (2002-2015)



Literature Review

Although it is not as popular as the profit-based analysis, non-performing loan (NPL) studies have also attracted the scholars. The studies about NPL can be divided into 3 main groups. The first one is based upon more macroeconomic theory and fed by the macroeconomic studies; the second group is the one in which the financial ratios based upon the balance sheet inputs are used. Because of the shortcomings, which are caused by the first two groups inefficiencies or narrow visions, the third one has been emerged in the literature. The third group is the combination of both financial ratios and macro economic variables. To explain the NPL, many scholars find the macroeconomic variable more fruitful (Berger and De Young, 1997). Some of them are more interested in the seasonal changes and crisis (Quagliariello, 2007). In addition, most of the researchers have used the GDP, interest rate volatility, unemployment rate as well as indices like the industrial production and stock market to explain the non-performing loan ratio (Louzis et al, 2010; Serwa, 2013; Dash & Kabra, 2010; Espinoza & Prasad, 2010; Chase et al, 2005; Saba et al 2015; Vogizas & Nikoladiou, 2011; Betancourt, 1999; Grennige & Grossvenor, 2010).

The second group, which was defined above is more interested in financial ratios to build up a linear or panel data type of econometric models to estimate and explain the non-performing loan ratio. Such scholars have used the variables like asset quality ratios, liquidity ratios, capital ratios and profit based ratios (Lu et al, 2005; Ghosh, 2015).

The third group has used both variables (market related and bank related) to explain the non-performing loans. Such researchers have preferred both bank related and market relate macro variables in order to increase the ability of the model to explain the changes in the non-performing loans. They believe that both internal factors that indicate bank management policies and activities can be controlled by the bank up to a certain level. Moreover, banks have no control over the macro variables and they have to accept it as an obligatory input (Klein, 2013; Boudriga et al, 2010; Espinoza & Prasad, 2010; Messai & Jouini, 2013).

For the Turkish banking sector, the number of the studies about non-performing loan is limited. Most of the researchers in Turkey have followed the third group explained above which states that the non-performing loan is the result of banks internal process as well as management initiatives plus the macro-economic market related variables which cannot be controlled by the bank itself (Cifter et al, 2009; Macit & Keçeli, 2012; Vardar & Özguler, 2015)

ANN literature has been generally concentrated on profit-based analysis in which the different type of machine learning models and methodologies are used. Moreover, although limited, some researchers are also concentrated on non-performing loan estimations. Some researchers have used the non-performing loan estimation as a complementary part of a different structure like rating or risk assessment system, whereas the others are directly concentrated on estimation of such ratio with ANN (Boan & Hai, 200; Lin, 2010; Poghosyan & Chiak, 2009; Männasoo et al, 2009; Malthora & Singh, 2007; Malthora & Malthora, 2007). As stated before, only limited studies are available in literature, which are based upon ANN to estimate the nonperforming loan ratio. More specifically; for the Turkish banking sector as well the development and investment banks; there is no such a research that estimates the non-performing loan ratio by means of the ANN models.

Considering the importance of Turkish economy as well as the Turkish banking sector, its growth and potential, every study on this banking group would be valuable. The non-performing loan in banking sector is extremely important as its relationship with other risks like liquidity and profit based management problems. There is strong shortcomings of the panel data and other deterministic econometric models and the wide open area for usage of ANN. Considering all, such a research aiming at explaining non performing loan in Turkish banking sector by using ANN would fill the gap and would be very useful for the practitioner and the scholars.

Table I: The Literature Summary on Non-Performing Loan

Research	**Macro Variables (Economy Spesific)**	**Micro Variables (Banks Spesific)**
Berger & De Young (1997)	Region Of The Bank	Capital Equity, Banks Effiiciency, Risk Weighted Assets,
Betacourt (1999)	House Prices, Credit Standards, Interest Rates	-
Chase et al (2005)	Treasury Bill, Consumer Price Index, Real Gdp	-
Lu et al (2005)	-	Gross Earning / Assets, Reatined Earnings/ Assets, Growth Rate, Projected Loan Ratio
Quagliariello (2007)	The Annual Growth Of Real GDP, Interest Rate On Long-Term (10-Year) Italian Treasury Bonds. Annual Appreciation/Depreciation Of The Stock Exchange Index, The Spread Between Loan And Deposit' Rates	Loan Growth, The Cost-To-Income Ratio, The Return On Assets , The Stock Of Non-Performing Loans / Total Loans, The Flow Of Non-Performing Loans At T / Total Performing Loans At T-1,
Dash & Kabra (2010)	GDP, Construction Expenditure, Foreign Exchange Reserve, Stock Market Indices, Stock Market Volatility, Foreign Exchange Rate, Repo Rate, Unemployment Rate, Lending Rate	-

Louzis et al (2010)	GDP, Unemployment Rate	Return on Assets, Return of Equity, Solvency Ratio, Loans to Deposits, Inefficinecy Ratio, Credit Growth, Relative Market Power, Relative Size
Grennidge & Gresvenor (2010)	GDP, Interest Rate, Consumer Price Index	Relative Size, Change in Total Loans
Boudriga et al (2010)	GDP, Industry State, Financial Development in a Country	CAR, Return on Asset, Foreign Ownership Ratio,
Espinoza &Krashad	Non-oil GDP Growth, VIX, Interest Rate	Equity, Expense / Assets, Loan Growth
Vogiazas & Nikolaidou (2011)	Total Gross External debt / GDP, Unemployment, Total Consumption, CPI, Trade Balance, M1,M2 Money Supply, Eurobor 3 Months Rate, Loans onProvision/Total Loans,Spread over German 10 years Bond, 10 Year Bond Rate	-
Saba et al (2012)	GDP, Interest Rate	Total Loan
Messai & Jouini (2013)	GDP, Unemployment Rate, Real Interest Rate	Return on Assets,Growth of Loans, Loan Loss Reserves
Jakubík & Reininger (2013)	Real GDP, Total Credit / GDP, Echange Rate, Stock Indices	-
Klein (2013)	Unempoyment Rate , Inflation, Echange Rate	Equity / Asset,Return on Asset, Loan to Asset
Skarica (2014)	Real GDP, Unemployment, Inflation, Nominal Exchange Rate, Total Loan Change	-
Ghosh (2015)	GDP, Public Debt, and changes in state housing price, inflation, unemployment rate	-

Yücemiş & Sözer (2011)	Industry Production Index, Exchange Rate	-
Macit & Keçeli (2012)	Inflation, GDP, Exchange Rate	Capital / Assets, Credit / Assets
Vatansever & Hepşen (2013)	Inefficiency Ratio, Debt Ratio, Return on Asset, Loan on Asset, CAR	Confidence Index, Consumer Price Index, Exchange Rate (EURO, USD), Stock Exchange Index, Industrial Production Index,M3 Money Supply, Gross Domestic Product, Interest Rate
Şahbaz & İnkaya (2014)	GDP, Private Fixed Capital Expenditure, Growth In Banking Sector	-
Abidoğlu & Aytekin (2015)	-	Net Interest Margin, Interest Rate on Credit, Total Credit / Total Saving, Solvency Ratio, CAR, Profit on Equity, Total Credit / Total Loans, Inefficiency Ratio, Total Credit / Total Assets, Provisions
Yağcılar & Demir (2015)	Growth, Inflation, Interest Rate	CAR, Credits / Savings, Solvency Ratio, ROA, Size, Net Interest Rate Margin, Credit Interest Income / Expenditure, Capital Structure
İslamoğlu (2015)	GDP, Interest Rate	-

When the listed recent studies are analyzed as seen in Table I, there are two groups of common variables. The first one resembles the macroeconomic effects on non-performing loans, whereas the second group includes the micro or company specific variables that denote the internal or micro effects. As market related variables, GDP, Industrial Production and Stock Market Indices and for outside the USA foreign exchange rates are more highlighted. One the other way around in order to explain the company or bank specific effects, financial ratios over the capital, loan growth, asset size and asset growth, profit are more preferred.

Data Set and the Methodology

According to the web site Turkish Supervisory Body, namely BDDK, there are 52 banks in Turkey with banking license, whose composition is given below Table II;

Table II: The Commercial and Ownership Structure of Turkish Banks

Capital Structure	Commercial Banks	Development and Investment	Participation Banks
Public Banks	3	4	1
Foreign Ownership	11	5	
Local Ownership	13	4	3
Operate as Branch Office	6		
Compulsorily Controlled By Public Bodies	1		1
Total	34	13	4

As it is seen from the table that there are totally 34 commercial and 13 development and investment banks 4 of whom are the public, 5 of whose shares are owned by foreign companies, 4 of whom are locally owned operating in Turkey.

In this research, the investment and development banks are chosen because of their strategic importance, the process of supporting economy by transferring the sources to the strategically important sectors, and their target market share, which is composed of the companies with relatively good governance and having solid investment projects. The total asset size of those banks is almost the %7 of the total banking sector in Turkey. Although it seems small, considering the total number of studies about those banks, it can be easily stated that there is a strong gap and a need for the academic studies about that banking group. The 13 investment and development banks in Turkey (according to the September 2015 data of the BDDK) are listed in Table III:

Table III: Public and Private Investment and Development Banks

PublicBanks
Development Bank of Turkey (Kalkinma Bankası)
TurkishExim Bank
İller Bank
Takas Bank

Private (LocalandForeignOwnership)
Diler Bank
Bank Pozitif
Aktif Bank
Pasha (Taib Bank)
MerillInc.
StandatChattered
TSKB* (PublicBanks has shareso; Public-Private)
Nurol Bank
GSD Bank

Selection of the variables to explain the non-performing loans in Turkish development and investment banks is the most important process. By following the procedure Khamis & Abdullah (2013) for NARX model, the past studies are analyzed and the most selected variables are preferred. Moreover; amongst all of these 13 banks, 11 of the banks were chosen except for the Standard Chattered and Merill Inc. because of their data inadequacy.

As stated before, the variables used in this study are grouped as macro or market related and micro or bank related variables just like the previous searches. The market related variables or called as macro variables, by following the indicated past studies above set as: GDP, Unemployment Rate, Stock Market Index, Industrial Production Index, and exchange rates as EUR/TRL, USD/TRL.

The micro or bank related variables, by following the procedure above, chosen as the financial ratios, which is used to define the banks financial situation. Under the light of past researches, the 3 main headings are set as, asset based ratios, profit based ratios, capital based ratios and risk measurement; totally 9 variables listed as; CAR ratio for the total risk taken, net profit / total capital, Liquid Assets / Total Assets, Total Capital / Total Assets, Received Loans / Total Assets, Total Credits / Total Assets, Non-Performing Loans /Total Credit, Net FX Position / Total Capital.

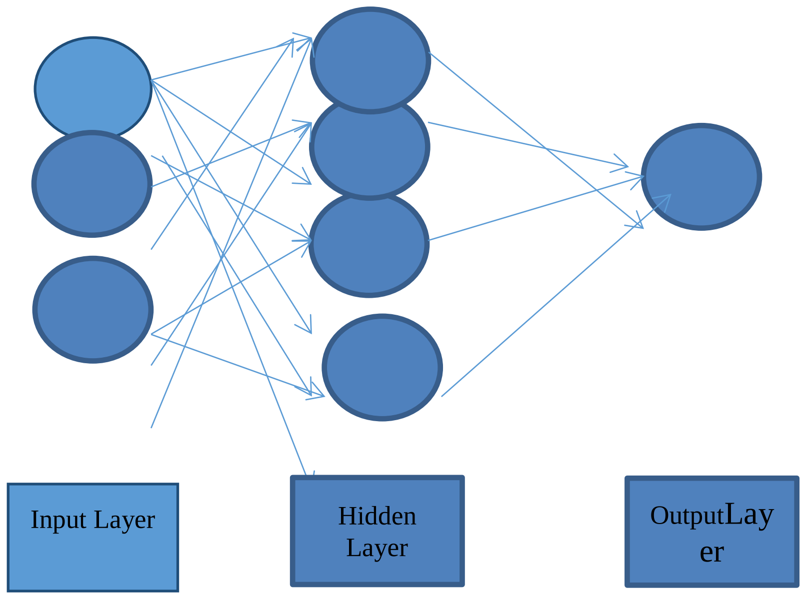
All of those macro and micro variables are downloaded from the Official Turkish Public Organizations web sites as TUİK (Turkish Institute of Statistics), Central Bank of Turkey, and Turkish Treasury. In variable set, except for the FX rates, all of the variables are announced quarterly. The return for FX rate is calculated quarterly for the harmonization between the variables.

For those 15 variables, in order to apply non-linear vector autoregressive ANN model, the normalization process is applied and all the variables are pushed to be between (-1) and 1. The Normalization process is simply done with the formula given below;

$$X_{(I)\ normalised} = \frac{X_{(I)\ normalized} - (X_{max} - X_{min})/2}{(X_{max} - X_{min})/2} \quad (1)$$

Amongst all of the other algorithms, the Backpropagation neural network (BPNN) is preferred as it is the most widely used learning algorithm and it is a popular technique easy to implement. The backpropagation network training is composed of three stages: a) feeding forward of the input training pattern, the backpropagation of the associated error, and the adjustment of the weights based upon the errors and the starting conditions (Laurene, 1994). BPNN structure has four main elements; 1-the network architecture determination, 2-hidden neuron number determination, 3-activation function optimization and 4-training algorithm optimization (Hagan et al., 1996). As shown in Figure 1, the network consists of three layers. The first layer, which is called as the input layer, is functioning like the independent variables in linear regression models that is triggered using the activation function. Whereas, the second layer which is called as hidden layer works as semi dependent variable. The last one, third layer is the output layer and it is very similar like the dependent variable in linear regression model. A network of these two-transfer functions can be trained to approximate any function.

Figure II: The Architectural Structure of the ANN



Nonlinear Autoregressive Network with Exogenous Inputs (NARX) which is used in this research to estimate the non-performing loan in Turkish development and investment banking sector; is a recurrent dynamic network, with feedback connections enclosing several layers of the network. That model is based upon the linear ARX model commonly used in time series modeling. Such model is defined also as recurrent neural architectures that is opposed to other recurrent neural models with limited feedback architectures (Chen, et. al., 1990). Such limited feedback architecture is the result of the output neuron instead of from hidden neurons. Just like done in this analysis, the NARX models are used in the system of identification area (Xie et al., 2009). Moreover; the NARX is reported to be much better at discovering the long-term dependency then classical neural networks (Diaconescu, 2008)

The General formula of NARX model is can be written as:

$$y_{(t+1)} = f\,[y_{(t)},\ldots,x_{(t-dy+1)};\, u_{(t-k)},\, u_{(t-k-1)},\ldots,\, u_{(t-k-du+1)}], \qquad (2)$$

$u_{(n)}$, $y_{(n)}$: denote, respectively, **the input** and output of the model at discrete time to step n under the condition that du ≥ 1, dy ≥ 1 and du ≤ dx, which are the input-memory and output-memory orders, respectively.
k (which should be k ≥ 0) is called as the delay term.

Again in this formula, f(·) is generally unknown and can be approximated, for example, by a standard multilayer perceptron (MLP) network. Under in our case, the resulting architecture can be called as a NARX network.

X_t (Vector of exogenous inputs) ------------→
$X_{(t-n(dx)\Delta t)}$, $X_{(t-n(dx)\Delta t+1,\ldots.)}$ (Vectors of delayed exogenous inputs) -------------→ Hidden Layer ----------
---→ $Y_{(t)}$
$Y_{(t-n(dy)\Delta t)}$, $Y_{(t-n(dy)\Delta t+1,\ldots.)}$ (Vectors of delayed regressed output) -------------→

Input and output regressors should be defined to get full benefits from the NARX network computational abilities. The input signal regressor, shown as$u_{(t)}$ is defined by the delay compatibility and shown as follows in NARX formula ;

$$U_{(t)} = X_{1(t)} = \{X_{(t)}, X_{(t-\tau)},\ldots, X_{(t-(dE-1)\tau)}\} \qquad (3)$$

where du = dE.
$U_{(t)}$,so called signal regressor, is composed of dE actual values of the observed time series, separated from each other of τ time steps. The output signal regressor $Y_{(t)}$ can be written as

$$Y_{*(t)} = \{X_{(t)},\ldots, X_{(t-dy-1)}\} \qquad (4)$$

Then, the NARX networks predictive mappings can be written as;

$$X_{(t+1)} = g[y_{*(t)}, u_{(t)}] = g[y_{sp(t)}, x_{1(t)}] \qquad (5)$$

where the nonlinear function g(.) is readily implemented through an multilayer perceptron trained with plain backpropagation algorithm.

In addition, during training, the inputs to the feed-forward network are just the real/true ones, not estimated ones, so the training process is more accurate. The network training function updates the weight and bias values according to Levenberg-Marquardt optimization. In general, in function approximation problems, for networks that contain up to a few hundred weights, the Levenberg-Marquardt algorithm will have the fastest convergence. This advantage is especially noticeable if very accurate training is required. However, as the number of weights in the network increases, the advantage of this algorithm decreases.

Data Analysis

This study has two main targets. As first, it aims to construct a model, which explains the nonperforming loan ratio in Turkish development and investment banks by using the ANN NARX model with the MATLAB tool called "NSTART". Secondly it aims to understand which variables are more efficient to make the estimation for non-performing loan; macro, micro or both. Then make a decision whether such efficiency changes based upon the ownership of the bank, public or private.

In the network modeling for each one of the 11 banks, out of the 42 data points (for each quarter) between December/2003-September/2015 are used, as all the variables were available in this time interval. Out of those 42 data points: 70% was used for training, 15% for validation and another 15% for testing. ANN–NARX model is run for each of the banks 3 times separately, for macro variables, then for micro variables and at last for macro and micro variables together. Such NARX models were also constructed for the 6 different hidden neuron between 5 to 10 and for 2 different lag periods 1 and 2 which means; for each bank, 6 (hidden neuron cases)*2 (lag cases)*3(variable groups : micro / macro /macro and micro together) =36 models were tried. For each variable group, the best model was selected based upon the MSE and R values just like the similar previous scientific studies. Out of the models with lower MSE and higher R, the valid one was decided upon the error autocorrelations (looking for no autocorrelation for lags) and performance graph (where the performance lines for training testing and validation are separated from each other which shows the better performance and acceptance).

For each one of the 11 banks, models estimate the non-performing loan ratio with macro variables, micro variables and with both micro and macro are listed below. Moreover the performance acceptance criteria are set as the MSE, R value, no error autocorrelation and performance results of data group (training, test and validity). As there are 3 variable groups, bank related “micro”, market related “macro” and their full combination “both”; there is a best model for each one of those variable groups. There are 11 banks to be analyzed (11*3=33 best models to be selected). Moreover, if there is autocorrelation between the error terms or the performance results of data groups are not separated, then the model cannot be accepted. Under that circumstance, according to MSE and R values, next best model is chosen as the best one.

Table IV: The ANN-NARX Results for Turkish Investment and Development Banks

Banks Name	**Aktif Bank**	ANN - NARX MODEL RESULTS				
Ownership Status	Private					
Model (Hidden Layer - Lag	Macro Model		Micro Model		Macro Micro Model	
	MSE (10e-4)	R	MSE	R	MSE	R
5-1	430	0.98	**25**	**0.99**	32	0.98
5-2	130	0.92	83	0.83	61	0.92
6-1	**80**	**0.94**	13	0.98	18	0.87
6-2	460	0.92	46	0.98	27	0.95
7-1	350	0.81	13	0.99	30	0.96
7-2	50	0.97	84	0.78	21	0.99
8-1	2300	0.39	31	0.97	29	0.99
8-2	100	0.96	19	0.99	**26**	**0.98**
9-1	290	0.91	36	0.86	240	0.93
9-2	27	0.98	54	0.93	33	0.81
10-1	420	0.96	11	0.60	7	0.96
10-2	140	0.99	36	0.91	42	0.95

Banks Name	**İller Bank**	ANN - NARX MODEL RESULTS				
Ownership Status	Public					
Model (Hidden Layer- Lag)	Macro Model		Micro Model		Macro Micro Model	
	MSE (10e-4)	R	MSE	R	MSE	R
5-1	10	0,72	1	0,98	**23**	**0,83**
5-2	2	0,86	3	0,75	29	0,44
6-1	27	0,36	15	0,87	27	0,68
6-2	36	0,28	4	0,76	8	0,72
7-1	**17**	**0,83**	**10**	**0,95**	71	0,64
7-2	18	0,66	22	0,76	122	0,47
8-1	81	0,67	13	0,80	1	0,91
8-2	106	0,78	11	0,24	61	0,85
9-1	29	0,66	14	0,17	36	0,61
9-2	181	0,76	1	0,92	63	0,39
10-1	106	0,47	21	0,90	94	0,89
10-2	14	0,97	15	0,18	24	0,56

Banks Name	**Diler Bank**	ANN - NARX MODEL RESULTS				
Ownership Status	Private					
Model	Macro Model		Micro Model		Macro Micro Model	
	MSE (10e-4)	R	MSE	R	MSE	R
5-1	19	0.98	46	0.98	24	0.98
5-2	10	0.99	77	0.56	99	0.92
6-1	110	0.96	73	0.99	12	0.98
6-2	160	0.91	**58**	**0.99**	**6**	**0.78**
7-1	**5**	**0.85**	84	0.98	2	0.99
7-2	110	0.91	62	0.99	61	0.92
8-1	11	0.99	67	0.99	81	0.89
8-2	6	0.99	111	0.96	1230	0.98
9-1	260	0.99	99	0.93	9	0.73
9-2	12	0.99	363	0.74	7	0.99
10-1	42	0.99	132	0.99	1109	0.99
10-2	160	0.99	310	0.99	782	0.74

Banks Name	**GSD**	ANN - NARX MODEL RESULTS				
Ownership Status	Private					
Model	Macro Model		Micro Model		Macro Micro Model	
	MSE (10e-4)	R	MSE	R	MSE	R
5-1	46	0.91	36	0.92	77	0.84
5-2	68	0.87	55	0.97	153	0.92
6-1	21	0.72	8	0.99	41	0.96
6-2	35	0.96	99	0.89	**27**	**0.87**
7-1	28	0.56	221	0.83	94	0.86
7-2	45	0.92	125	0.88	29	0.93
8-1	28	0.98	155	0.89	115	0.66
8-2	**13**	**0.71**	467	0.96	167	0.77
9-1	34	0.89	68	0.97	48	0.94
9-2	23	0.71	64	0.92	67	0.78
10-1	96	0.89	63	0.95	64	0.95
10-2	161	0.98	160	0.86	121	0.72

Banks Name	**Bank Pozitif**	ANN - NARX MODEL RESULTS				
Ownership Status	Private					
Model (Node-Lag)	Macro Model		Micro Model		Macro Micro Model	
	MSE (10e-4)	R	MSE	R	MSE	R
5-1	278	0,86	456	0,78	642	0,8
5-2	**260**	**0,95**	653	0,89	**149**	**0,94**
6-1	756	0,82	140	0,39	218	0,94
6-2	375	0,91	**355**	**0,71**	286	0,85
7-1	581	0,79	403	0,83	502	0,67
7-2	597	0,9	645	0,51	522	0,73
8-1	587	0,8	623	0,81	356	0,99
8-2	1332	0,76	661	0,89	456	0,76
9-1	472	0,79	344	0,8	308	0,86
9-2	668	0,92	755	0,47	639	0,54
10-1	983	0,92	544	0,69	249	0,9
10-2	499	0,68	383	0,86	1000	0,54

Banks Name	**Exim Bank**	ANN - NARX MODEL RESULTS				
Ownership Status	Public					
Model (Node-Lag)	Macro Model		Micro Model		Macro Micro Model	
	MSE (10e-4)	R	MSE	R	MSE	R
5-1	8	0,99	8	0,99	2	0,99
5-2	12	0,95	11	0,99	46	0,95
6-1	6	0,99	4	0,99	18	0,99
6-2	46	0,99	24	0,95	35	0,98
7-1	9	0,99	25	0,99	48	0,84
7-2	**7**	**0,95**	55	0,99	28	0,98
8-1	17	0,99	11	0,99	**23**	**0,97**
8-2	18	0,98	64	0,69	25	0,7
9-1	16	0,99	18	0,99	126	0,96
9-2	14	0,99	100	0,91	31	0,94
10-1	50	0,91	**6**	**0,99**	8	0,99
10-2	41	0,95	29	0,95	243	0,99

Banks Name	**TSKB**	ANN - NARX MODEL RESULTS				
Ownership Status	Public-Private					
Model (Node-Lag)	Macro Model		Micro Model		Macro Micro Model	
	MSE (10e-4)	R	MSE	R	MSE	R
5-1	124	0,98	**10**	**0,99**	23	0,98
5-2	56	0,95	21	0,99	56	0,88
6-1	316	0,92	71	0,97	**44**	**0,98**
6-2	**72**	**0,99**	276	0,94	67	0,88
7-1	152	0,86	36	0,99	117	0,89
7-2	362	0,82	51	0,96	159	0,94
8-1	298	0,82	114	0,87	71	0,99
8-2	26	0,96	19	0,98	206	0,93
9-1	468	0,77	6	0,99	56	0,98
9-2	252	0,84	26	0,97	36	0,97
10-1	106	0,95	30	0,98	216	0,89
10-2	109	0,93	58	0,97	52	0,97

Banks Name	**NUROL**	ANN - NARX MODEL RESULTS				
Ownership Status	Private					
Model (Node-Lag)	Macro Model		Micro Model		Macro Micro Model	
	MSE (10e-4)	R	MSE	R	MSE	R
5-1	326	0,9	609	0,75	229	0,6
5-2	144	0,92	**206**	**0,92**	**184**	**0,9**
6-1	905	0,75	476	0,8	851	0,6
6-2	**178**	**0,75**	110	0,96	393	0,79
7-1	114	0,93	992	0,41	643	0,82
7-2	594	0,93	247	0,84	521	0,84
8-1	534	0,8	399	0,79	474	0,67
8-2	344	0,85	697	0,83	418	0,98
9-1	717	0,48	259	0,69	1118	0,21
9-2	997	0,61	512	0,65	549	0,5
10-1	288	0,93	214	0,55	41	0,97
10-2	911	0,68	562	0,79	399	0,9

Banks Name	**PASHA /TAIB**	ANN - NARX MODEL RESULTS				
Ownership Status	Private					
Model (Node-Lag)	Macro Model		Micro Model		Macro Micro Model	
	MSE (10e-4)	R	MSE	R	MSE	R
5-1	472	0,24	499	0,74	743	0,58
5-2	2463	0,94	3182	0,9	387	0,62
6-1	317	0,76	967	0,84	337	0,95
6-2	2926	0,33	8	0,87	711	0,84
7-1	8	0,96	893	0,73	1916	0,98
7-2	**157**	**0,96**	7	0,96	1716	0,23
8-1	4087	0,65	**301**	**0,66**	302	0,91
8-2	5	0,99	606	0,99	2828	0,71
9-1	1178	0,63	2555	0,71	306	0,52
9-2	377	0,68	1123	0,53	1403	0,84
10-1	199	0,35	276	0,63	**202**	**0,91**
10-2	1020	0,47	698	6,98	304	0,77

Banks Name	**TAKAS**	ANN - NARX MODEL RESULTS					
Ownership Status	Public						
Model (Node-Lag)	Macro Model		Micro Model		Macro Micro Model		
	MSE (10e-4)	R	MSE	R	MSE	R	
5-1	273	0,91	60	0,91	204	0,77	
5-2	258	0,77	**0,04**	**0,95**	81	0,84	
6-1	60	0,98	456	0,47	35	0,97	
6-2	130	0,97	250	0,46	**0,99**	**0,99**	
7-1	153	0,62	35	0,69	151	0,79	
7-2	87	0,99	444	0,7	71	0,87	
8-1	34	0,87	271	0,41	367	0,52	
8-2	419	0,91	0,49	0,97	221	0,56	
9-1	106	0,74	391	0,4	39	0,8	
9-2	277	0,88	11	0,22	600	0,92	
10-1	**0,72**	**0,89**	194	0,95	54	0,91	
10-2	270	0,63	82	0,8	352	0,78	

Banks Name	**Kalkınma B.**	ANN - NARX MODEL RESULTS				
Ownership Status	Public					
Model (Node-Lag)	Macro Model		Micro Model		Macro Micro Model	
	MSE (10e-4)	R	MSE	R	MSE	R
5-1	209	0,92	140	0,83	214	0,92
5-2	136	0,91	305	0,96	**6**	**0,98**
6-1	140	0,91	292	0,38	175	0,90
6-2	222	0,9	591	0,86	7	0,91
7-1	161	0,99	190	0,91	4	0,88
7-2	10	0,94	321	0,78	44	0,63
8-1	150	0,87	21	0,99	54	0.96
8-2	**82**	**0,87**	391	0,8	149	0,88
9-1	306	0,99	177	0,7	892	0,56
9-2	116	0,89	732	0,98	697	0,76
10-1	311	0,84	222	0,9	419	0,54
10-2	147	0,8	**68**	**0,97**	421	0,93

The best model of the each variable group for each bank has been labeled with the bold character. The main criteria for the best model are as indicate before the MSE and R values. However, as stated before, in order a model to be valid, it must show better performance and there should be no autocorrelations between lag error terms. If one of those conditions or both is not satisfied, the model is not accepted as the best one as.

As a summary for each bank the best models are listed in Table V;

Table 5: The Best Models for Each of Investment and Development Bank

Banks Name	Ownership	Macro Model	Micro Model	Mic-Mac Model	Best Model
Aktif Bank	Private	6-1	5-1	8-2	5-1 (Micro)
İller Bank	Public	7-1	7-1	5-1	7-1 (Micro)
Diler Bank	Private	7-1	6-2	6-2	7-1 (Macro)
GSD	Private	8-2	10-1	6-2	8-2 (Macro)
Bank Pozitif	Private	5-2	6-2	5-2	5-2 (Mic - Mac)
Exim Bank	Public	7-2	10-1	8-1	10-1 (Micro)
TSKB	Public	6-2	5-2	6-1	5-2 (Micro)
Nurol Bank	Private	6-2	5-2	5-2	6-2 (Macro)
Pasha / TAIB	Private	7-2	8-1	10-1	7-2 (Macro)
Takas Bank	Public	10-1	5-2	6-1	5-2 (Micro)
Kalkınma Bank	Public	8-2	10-2	5-2	5-2 (Mic-Mac)

Out of 4 public banks, 3 of them have the best model under the micro variables; only one of them has the best model with macro and micro variables. For the remaining 7 private banks, only one of them has the best model with macro and micro variables together and another one with micro variables. That means %75 of the public banks have the best model with micro variables and %77 of the private bank have the best model with only macro variables. Under such case we can reach three interesting results two of which are related to Turkish development and investment banking non-performing loan estimation;

1. For the public banks, the models with bank related micro variables are more efficient to estimate the non-performing loans

2. For the private banks, the models with market related macro variables are more efficient to estimate the non- performing loans

3. To build a more complex model with many variables as well as many hidden nodes doesn't mean to get a model with better results, as the models with different numbers of layers have the best results.

Conclusion

When the management style, the regulation over the banks, the available financial sources and public supports are considered, in Turkey, the private and public banks are strongly discriminated. Most of the public banks get the guarantee of the government more easily when they want to reach the international financial sources or partnership for international project agreements. Under liquidity distress, they get more support from the public institutions as in 2001 Ziraat Bank case. Such banks have different internal and external motives, as the public banks can be used or directed by the government for the short and long-term economical and financial goals or programs. The private banks attitudes are generally shaped by the free market conditions. Considering the structural, political and strategic differences between these two banking group, it can be easily stated that the variables which effect the non-performing loan would be different. By applying the ANN –NARX model of those banks (both public and private development and investment banks) separately, it is seen that such a statement is valid. Although most of the private banks non-performing loan is better estimated with the model built with macro variables, the public banks non-performing loan is better estimated with the models with micro or bank related variables. Moreover, according to the results of this research, it can be easily stated that the ANN-NARX models work very efficiently to estimate NPL for each bank. The models with more variables don't mean better results for estimation. In order to estimate the non-performing loan for a development and investment banks, it is very important to determine the bank type first and then concentrate on the model. The group of the variables in fact points out the management style, internal factors and their close relationship with the market, which make the researcher to classify the banks as public and private.

REFERENCES

Abdioğlu N., Aytekin S. (2016), "Takipteki Kredi Oranını Etkileyen Faktörlerin Belirlenmesi: Mevduat Bankaları Üzerinde Bir Dinamik Panel Veri Uygulaması", *İşletme Araştırmaları Dergisi*, 8(1):126-141.

Alam, P., Booth, L. K. and T. Thordason. (2000), "The Use of Fuzzy Clustering Algorithm and Selforganizing Neural Networks For Identifying Potentially Failing Banks: An Experimental Study", *Expert Systems with Applications*, 18:185-199.

Baoan, Y., Hai J. (2001), "Artificial Neural Network Based on Credit Risk Early Warning", *Journal of Systematic Engineering Theory And Practice*, 2001, (5):70-74.

Berger, A.N., De Young R., (1997), "Problem Loans and Cost Efficiency in Commercial Banking", *Journal of Finance and Banking* , 21:849-870.

Betancourt, L., (1999). "Using Markov Chains to Estimate Losses from a Portfolio of Mortgages", *Review of Quantitative Finance and Accounting*, 12(3), 303-317.

Boudriga, A., Neila T., (2009), "Banking Supervision and Nonperforming Loans: A Cross-Country Analysis", *Journal of Financial Economic Policy*, 1(4):286-318.

Chase K., Greenidge T., Moore W., Worrell D., (2005), "Quantitative Assessment of a Financial System – Barbados", *IMF Working Paper*, 05/76.

Chen, S, Billings, S. A. & Grant, P. M., (1990), "Non-Linear System Identification Using Neural Networks", *International Journal of Control Systems*, 51(6):1191-1214.

Cifter A., Yılmazer S., Cifter E., (2009), "Analysis of Sectoral Credit Default Cycle Dependency with Wavelet Networks: Evidence From Turkey", *Economic Modelling*, 26(6):1382-1388.

Dash, M., Kabra, G., (2010), "The Determinants of Non-Performing Assets In Indian Commercial Bank: An Econometric Study", *Middle Eastern Finance and Economics*, 7:94-106.

Diaconescu, E., (2008), ”The Use of NARX Neural Networks To Predict Chaotic Time Series”,*Wseas Transactions on Computer Research*, 3(3):182-191.

Eichengreen, B., (2002), *Financial Crises*, Oxford University Press, New York, NY.

Espinoza R., Prasad A., (2010), “Nonperforming Loans in the GCC Banking System and Their Macroeconomic Effects”, *IMF Working Papers*, 1:24-33.

Fred A., (2014), “Affects of Selected Bank Specific Factors on Non Performing Loans Amongst Commercial Banks In Kenya”, *Journal African Business Studies*, 15(3):86-103.

Ghosh, A., (2015), “Banking-Industry Specific and Regional Economic Determinants of Non-performing Loans: Evidence from US States”, *Journal of Financial Stability*, 20:93-104.

Grennidge K., Grossvernor T., (2009), “Forecasting Non-Performing Loans in Barbados”, *Annual Review Seminar Research*, Department Central Bank of Barbados.

Grennige K., Grossvenor T., (2010), “Forecasting Non-Performing Loans in Barbados”, *Journal of Business Finance and Economics in Emerging Economies*, 5(1):1006-1066.

Hagan, M.T., Demuth H.B., Beale, M.H., (1996), “Neural Network Design” 1st Edn., PWS Publishing Company, Boston.

İslamoğlu M., (2015), “Türk Bankacılık Sektöründe Takipteki Kredilerin Makroekonomik Etkileri”, *Uluslararası Alanya İşletme Fakültesi Dergisi International*, 7(1):221-229.

Jakubík, P., Reininger, T., (2013), “Determinants of Nonperforming Loans in Central, Eastern and Southeastern Europe”, *Focus on European Economic Integration Oesterreichische Nationalbank*, 3: 48-66.

Karahanoglu I., (2015), “Türkiyedeki Kalkınma Bankalarının Sermaye Yeterlilik Rasyolarının Markov Zincirleri Yöntemi İle Tahmin Edilmesi”, *Journal of International Social Reserach*, 8(41):1236-1246.

Khamis A., Abdullah S.N.S.B., (2014), "Forecasting Wheat Price Using Backpropagation and NARX Neural Network", *The International Journal Of Engineering And Science*, 13(1):19-26.

Klein, N., (2013), "Non-Performing Loans in CESEE; DeterminantsandImpact on MacroeconomicPerformance", *IMF WorkingPapers* 13/72.

Laurene, F., (1994), *Fundamentals of Neural Networks: Architectures, Algorithm and Applications*, United States: Florida Institute of Technology.

Louzis D.P., Voulds A. T., Metaxas V. L., (2012), "Macroeconomic and Bank-Specific Determinants of Non-Performing Loans in Greece: A Comparative Study of Mortgage, Business and Consumer Loan Portfolios", *Journal of Banking & Finance*, 36(4):1012-1027.

Lu J., Bolton, B., & Bhagat S., (2015), "Size, leverage, and risk-taking of financial institutions", *Journal of Banking & Finance*, 59, 520-537.

Macit, F., Keçeli, B., (2012). "Takipteki Kredi Oranını Etkileyen Faktörler: Türkiye'de Katılım Bankaları Örneği", *Avrasya İncelemeleri Dergisi*, 1,(1):193-207.

Malthora R., Malthora D.K., (2003), "Evaluating Consumer Loans with Neural Network", *Omega*, 31(2):83-96.

Malhotra, P., & Singh, B., (2007), "Determinants of internet banking adoption by banks in India", *Internet Research*, 17(3), 323-339.

Männasoo, K., Mayes, D. G., (2009), "Explaining Bank Distress in Eastern European Transition Economies", *Journal of Banking & Finance*, 33(2):244-253.

Messai A., (2013), "Macro Determinants of Non-performing Loan", *International Journal of Economics and Financial Issues*, 3(4):852-860.

Messai, A. S., & Jouini, F., (2013), "Micro and macro determinants of non-performing loans", International journal of economics and financial issues, 3(4), 852.

Miletic, M., & Miletic, S., (2015), “Performance of Value at Risk models in the midst of the global financial crisis in selected CEE emerging capital markets”, *Economic Research-Ekonomska Istraživanja*, 28(1), 132-166.

Ozcan Ş.K., Papanionnau E., Pem F., (2013), “Global Banks and Crisis Transmission”, *Journal of International Economics*, 89(2):495-510.

Poghosyan, T., Cihák, M., (2009), “Distress in European Banks: An Analysis Based on a New Dataset”, *IMF Working Paper* - No. 09/9.

Prasanna K., (2014), “Determinants Of Non-Performing Advances in Indian Banking”, *System 3rd International Conference On Management / Behavioral Sciences And Economics Issues* (ICMBSE'2014).

Quagliariello, M., (2006), “Banks' Riskiness over the Business Cycle: A Panel Analysis on Italian Intermediaries”, *Bank of Italy Economic Research Paper*, No. 599.

Saba I., Rehana K., Muhammad I., (2012), “Determinants of Nonperforming Loans: Case of US Banking Sector”, *International Journal of Banking and Finance*, 44:479-488.

Serwa D., (2013), “Measuring Non-Performing Loans During (and After) Credit Booms”, *Central European Journal of Economic Modelling and Econometrics*, 5(3):163-183.

Skarica B., (2013), “Determinants of Non-Performing Loans in Central and Eastern European Countries”, *Financial Theory and Practice*, 38 (1):37-59.

Şahbaz A., İnkaya A., (2010), “Türk Bankacılık Sektöründe Sorunlu Krediler ve Makro Ekonomik Etkileri”, *Optimum Ekonomi ve Yönetim Bilimleri Dergisi*, 1(1):68-85.

Vardar G., Özgüler İ.C., (2015), “Takipteki Krediler, Makroekonomik ve Banka Özellikli Faktörler Arasındaki Uzun ve Kısa Dönemli İlişkiler: Türkiye için Ampirik bir Analiz”, *Ege Academic Review*, 15(3):13-325.

Vatansever M., Hepşen A., (2013), “Determining Impacts on Non-Performing Loan Ratio in Turkey”, *Journal of Finance and Investment Analysis*, 2(4):119-129.

Vogizas S., Nikolodau E., (2011), "Investigating the Determinants of Nonperforming Loans in The Romanian Banking System: An Empirical Study with Reference to the Greek Crisis", Economic Research International, 27(3):136-149.

Xie, H., Tang, H. & Liao, Y.H., (2009) , "Time Series Prediction Based on NARX Neural Networks: An Advanced Approach", *Proceeding of the International Conference on Machine Learning and Cybernetics* / IEEE Xplore Press, Baoding:1275-1279.

Yağcılar, G. G., Demir, S., (2015), "Türk Bankacılık Sektöründe Takipteki Kredi Oranları Üzerinde Etkili Olan Faktörlerin Belirlenmesi", *Uluslararası Alanya İşletme Fakültesi Dergisi*, 7(1).

Yücemiş B.T., Sözer İ.A., (2011), "Bankalarda Takipteki Krediler: Türk Bankacılık Sektöründe Takipteki Kredilerin Tahminine Yönelik Bir Model Uygulaması", *Finansal Araştırmalar ve Çalışmalar Dergisi*, 3(5):43-57.