2nd World Conference On Business, Economics And Management - WCBEM 2013

Macroeconomic Modelling Of Credit Risk For Banks

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Abstract

This study aims to explore the relations between bank credit risks and macroeconomic factors. We employ a set of variables including the inflation rate, interest rate, the ISE-100 index, foreign exchange rate, growth rate, M2 money supply, unemployment rate, and the credit risk represented by the ratio of non-performing loans to total loans (NPL) for Turkey during the January 1998 and July 2012 period. The general-to-specific modelling methodology developed by Hendry (1980) was employed to analyze short-run dynamic intervariable relationships, while Engle-Granger (1987) and Gregory-Hansen (1996) methodologies were used to analyze long-run relationships. In both methods, growth rate and ISE index are the variables that reduce banks' credit risk in the long run, while money supply, foreign exchange rate, unemployment rate, inflation rate, and interest rate are the variables that increase banks' credit risks. The specific model demonstrated that the previous period's credit risk has a significant impact on the current period's credit risk.

Keywords: Credit Risk, Engle-Granger Method, Gregory-Hansen Method, Hendry Method;

1. Introduction

Financial institutions and banks need certain criteria to make decisions and evaluate the decisions made in rapidly growing financial markets. Among these criteria, risk is the most important one. Risk is the possibility of facing undesired circumstances (IMKB, 1999:476). From the perspective of banks, risk denotes failure instead of achieving success. Successfully managed risk is a crucial instrument that increases a bank's profitability (Öker, 2007:30).

The most important risk that banks are exposed to is credit risk, which involves loans that are not paid back. Credit risk mainly refers to the possibility of loss for a bank due to the inability of loan debtors to fulfill on time or completely their obligations they have assumed as part of their contracts with the bank (these obligations usually involve the repayment of principal debt and interest to the bank on predetermined dates) (Altıntaş, 2012). Credit risk that banks are exposed to has two primary components, which are systematic and unsystematic credit risks. Systematic risk stems from the variability of economic, political, and social life and affects all financial (monetary and capital) markets and all securities (financial assets) traded in markets. Unsystematic credit risk, on the other hand, is the risk created by a firm or the characteristics of the industry in which the firm operates. Factors such as ill management, technological developments, new inventions, and changes in consumer preferences may lead to unsystematic volatility. Financial, management, operational, and industrial risks are unsystematic risks

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(Tuna, 2009). Systematic risks could be classified as market risk, political risk, inflationary risk, interest rate risk, operational risk, and exchange rate risk. Exchange rate risk involves the changes that may occur in assets or liabilities as a result of the changes in exchange rate. Interest rate risk is defined as the possibility that the overall increase in the market interest rate. Changes in market interest rates affect the prices of securities (financial assets). Inflationary risk refers to the uncertainty of expected returns from investments in the face of inflation (Dağlı, 2004; 325). Political risk defines the changes occurring in financial asset prices and returns due to the changes in political conditions. Operational risk denotes the risk of losses arising from inadequate or failed internal processes, people, and systems or external factors. Market risk is the risk of loss resulting from changes in the value of financial assets and consists of components such as interest rate risk, exchange rate risk, and operational risk, which are all outside the control of investors (Demireli, 2007).

In a conjuncture in which macroeconomic factors pursue an unfavorable course, the principal component that triggers credit losses is systematic credit risk. Since systematic credit risk mainly stems from economy-wide developments, a significant correlation is expected between systematic credit risk and macroeconomic factors. The ability of macroeconomic factors to explain systematic credit risk also varies across industries and sectors. However, although the ability to explain systematic credit risk varies across countries and sectors, macroeconomic variables such as GDP growth rates, interest rate, inflation rate, unemployment rate, foreign exchange rates, rates of public and private spending and saving, and monetary magnitudes are the major factors that could explain systematic credit risk (Altıntaş, 2012:67).

Various models have been developed to model credit risk for banking and have been put into implementation by banks. Among such models, the Credit Portfolio View (CPV) model is an approach that is commonly used for modeling banks' credit risks employing macro variables (Wilson, 1997a; 1997b; 1998). In the present study, by assuming that improved macroeconomic conditions will reduce credit risks, the macroeconomic variables with possible impact on credit risks were identified and an econometric model was established.

This study is composed of five sections. The second section explains the CPV model; the third section provides information about the econometric techniques used; the fourth section involves regression estimation; and the last section presents the interpretation of the analysis results and offers suggestions.

2 . Credit Portfolio View (CPV) Model

Credit Portfolio View is based upon the argument that default and migration probabilities are not independent of the business cycle. The 'unconditional' migration matrix needs to be adjusted for the state of the economy and the business cycle. This is understandable as during boom times default probabilities run at lower than the long term average that is reflected in the 'unconditional' migration matrix; and conversely during recessions default probabilities and downward migration probabilities run lower than the longer term average. This effect is more amplified for speculative grade credits than for investment grade credits as the latter are more stable even in tougher economic situations. This adjustment to the migration matrix is done by multiplying the unconditional migration matrix by a 'factor' that reflects the state of the economy. If *M* be the unconditional transition matrix, then *M x Factor* is the Conditional transition matrix.

The factor is just the conditional probability of default in period *t* divided by the unconditional (or historical) probability of default in the same period. This is expressed as follows:

$$M_t = M\left(\frac{P_{jt}}{\phi P_{jt}}\right)$$

where *M* is the unconditional transition matrix, and $P_{j,t}$ is the conditional probability of default in period t, and $\phi P_{j,t}$ is the unconditional probability of default in period t.

$P_{j,t}$ is a logit function and takes values between 0 and 1. This is exactly what we need for something to be considered as a probability.

$$P_{j,t} = \left(\frac{1}{1 + e^{-Y_{jt}}} \right) \tag{1}$$

Here, $Y_{j,t}$ is an index value derived using a multi-factor regression model that considers a number of macro economic factors, j representing the industry and t the time period. $P_{j,t}$ varies between 0 and 1, and represents the probability of default for speculative grade issuers (Parek, 2010). From equation (1), the value of macro index given default rate is calculated as:

$$Y_{jt} = \ln \left(\frac{1 - P_{jt}}{P_{jt}} \right) \tag{2}$$

In order to find the empirical link to macro variables, the transformed default rate (i.e. macro index) is assumed to be determined by a number of macro variables, as shown by equation 3.

$$Y_{j,t} = \beta_{j0} + \beta_{j1} X_{1\,t} + \beta_{j2} X_{2\,t} + \beta_{j3} X_{3\,t} + \ldots\ldots + \beta_{jn} X_{n\,t} + u_{jt} \tag{3}$$

where βj is a set of regression coefficients, X_{it} (i = 1, 2,…,n) is the set of explanatory macroeconomic factors (eg GDP, interest rates etc.), and u_{jt} is a random error assumed to be independent and identically normally distributed. The equations (1) to (3) define the relationship between sectoral default rates and macro variables (Küçüközmen & Yüksel, 2006).

3. Analytical Study
3.1. Methods Used
3. 1.1. Gregory-Hansen Method

Structural breaks in stationary time series result in non-rejection of the 'non-stationarity' hypothesis or induce unit roots in those series. Perron (1989) and Hendry & Neale (1991) showed in their studies that unit root tests are less powerful in series with structural breaks. This also applies to cointegration tests. Hansen (1992) and Gregory-Hansen (1996) developed tests to detect structural breaks in cointegrated vectors.

The standard test for cointegration are not appropriate in the case of an economic regime change. Hence, Gregory-Hansen(1996) have developed residual-based tests for cointegration which allow for the possibility of structural change. They propose extensions of ADF*, Z_α and Z_t test for cointegration and derive the asymptotic distributions of these test statistics. The level shift model of, Gregory- Hansen(1996) takes the form :

$$Y_{1t} = \mu_1 + \mu_2\, \Phi_t + \alpha\, Y_{2t} + e_t \qquad\qquad t = 1,2\ldots n \tag{4}$$

where $\Phi_t =1$ (t > [n τ]), τ ∈ (0,1) is an unknown parameter denoting the relative timing of the change point, 1(.) is the indicator function, and [ ] denotes integer part. The ADF statistic to test the nonstationarity of the residuals in (1) at τ yields Gregory- Hansen's ADF* tests :

$$ADF^* = \inf_{\tau \in t} ADF(\tau) \tag{5}$$

For each τ, the test statistics for cointegration are calculated. Following the procedure by Gregory- Hansen (1996), it is computed the test statistic for each break point in the interval ([0.15n], [0.85n]). The test statistic described in (5) provides a tool for analyzing cointegration regression with a regime shift. The smallest value of the ADF(τ) across all possible break points is searched because small values of the test statistic provide evidence against the null hypothesis of no cointegration (Yurdakul & Akçoraoğlu, 2005:26).

3.1.2. General-to-Specific Modeling Method

Based on the Hendry method, it consists of five stages (Hendry, 1980; Pagan, 1987).

1. Based on the assumptions of economic theory, a general model is formulated that encompasses all the variables proposed by the equilibrium relationship of the relevant theory.

2. The model is reparametrized to arrive at independent or exogenous variables that are as orthogonal as possible to be interpreted in terms of long-term equilibrium.

3. The model is simplified to get the smallest version consistent with the model's dataset.

4. In order to detect the weaknesses of the model formulated in the previous stage, analyses are performed on the obtained error terms and the model's estimation power.

5. The model and its alternatives are compared using "nested/non-nested" tests to determine whether there is a better rival model in statistical terms.

The general model is usually defined as "Autoregressive Distributed Lag Model" (ADL) The general model has the following form:

$$Y = \sum_{j=1}^{k} \alpha_j Y_{t-j} + \sum_{j=0}^{k} \beta_j X_{t-j} + \sum_{j=0}^{k} \delta_j Z_{t-j} + \ldots\ldots + u_t \qquad (6)$$

where care should be taken to avoid low degree of freedom when identifying the lag number k. Lag numbers are identified by using the Akaike Information Criteria (AIC) and Schwarz Information Criterion (SC) for the estimated models. In the remaining stages of the Hendry method, we reach the simplest and the most appropriate model by subjecting the general model to the reparametrization and simplification processes.

3.2. Definition of the Variables

In this study, a model was established in which bank credit risks are associated with macroeconomic variables. Several studies have been carried out on the subject and are summarized below.

Alves (2005) and Shahnazarian & Sommer (2007) pioneered the literature on the analysis of the interaction between default probabilities and macro variables using the VAR method. The authors found cointegration between expected default frequency and macro variables, reporting a significant correlation between short-term interest rates, economic growth, and inflation and default frequencies. Distinguin et al. (2006) analyzed probabilities of default for the banking system and macro economic variables and found that the extent to which bank liabilities are based on market data is important in the effectiveness of default probability. On the other hand, in a study exploring the relation between macro economic variables and the probabilities of default for Dutch firms, Simons & Rolwes (2008) found a negative relation between economic growth, oil prices and probability of default. They also reported that the interest rate and exchange rate are positively related to the probability of default in certain sectors. Castren et al. (2008) examined the relations between the expected default frequencies and economic growth, exchange rates, oil prices, and asset prices for euro area countries (Güngör, 2009). As for the research conducted by Central Banks, The Central Bank of Austria (2002), used inflation rate, Austrian stock market index, short-term interest rates and oil prices to explain default rate, while in another study, the Central Bank of Finland (2004) estimated six linear credit risk equations in which a macro index obtained after the logistic transformation of default rates for six economic sectors was used as the dependent variable. Wong, Choi & Fong (2006) from Hong Kong Monetary Authority logistically used the ratio of the amount of loans that have been overdue for more than three months to the total amount of loans as the dependent variable. GDP, interest rate, and property price index were employed as the independent variables. In their study, Otani, Shiratsuka, Tsurui & Yamada (2009) from the Central Bank of Japan established a macro model consisting of the variables of real GDP, consumer price index, total amount of loans, nominal exchange rate, and interest rate. Avouyi-Dovi, Bardos, Jardet, Kendaoui & Moquet (2009) from the Central Bank of France set up a VAR model for the macroeconomic index obtained through the logistic transformation of historical default rates for the manufacturing sector. They used GDP, interest rate and credit spreads which represent the difference between corporate bonds and risk-free interest rates as their independent variables (Altıntaş, 2012: 106). Also, in an empirical study examining seven EU countries, Rinaldi & Sanchis-Arellano (2006) concluded that inflation rate, the ratio of financial assets to disposable income, disposable income itself, the ratio of household debt

to household disposable income, and real lending interest rates were important variables affecting non-performing loans. Jakubik & Schmieder (2008) investigated the impact of unemployment rate, nominal and real interest rates, inflation rate, interest rate gap, real GDP growth rate, output gap, the ratio of loans to GDP, and the ratio of interest paid to disposable income upon non-performing loans (Tekirdağ, 2008). In their study, Küçüközmen & Yüksel (2006) estimated regressions including eleven different macroeconomic variables to explain sectoral default probabilities and modeled the macroeconomic variables using ARIMA models. In another study, Altıntaş (2012) used the index series obtained by the logistic transformation of total tracking rates as the dependent variable to represent credit risk and GDP, interest rate, inflation rate, unemployment rate, and exchange rates as explanatory variables. As it is clear from the literature that the researchers either use a macroeconomic index series formed by transformation into logistic form using default rates or a macroeconomic index series obtained through the transformation in logistic form instead of default rates as a variable representing credit risk. Certain studies used arrears as their dependent variable. As explanatory variables, they often chose GDP, inflation rate, interest rate, unemployment rate, and exchange rate.

The present study employs "the ratio of non-performing loans to total loans" (NPL) as the variable representing credit risk. This ratio serves as the main indicator of the losses which banks are exposed to due to credit risk. The ratio is found to increase during periods of increased financial fragility and reduced economic activity.

Graph 1 shows the course of NPL series between 1998.01 and 2012.07.

Graph 1: The Course of NPL Series between 1998.01 and 2012.07
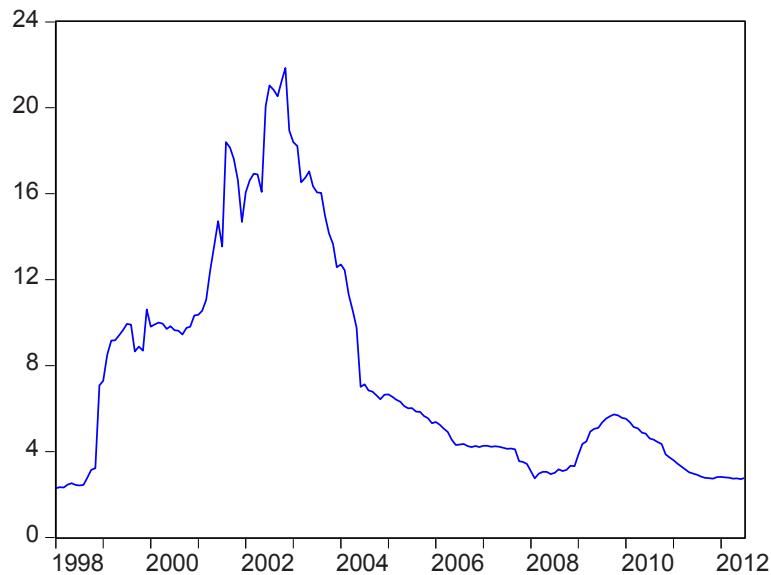
In Graph 1, there is a gradual increase in the NPL series between 1999 and 2003. This period covers the 1999, 2001, and 2002 crises, which had a deep impact in Turkey and involved the bank crisis. The NPL series started to decline after 2003. However, the 2008 crisis led to an increase in the NPL series, which again fell into a decline after 2010. Such periods of crisis witnessed a disruption in Turkey's macroeconomic balance, an observed increase in the currency and interest risk that the real sector is exposed to, and a decline in capacity utilization rate and industrial production in parallel to reduced domestic or foreign demand. As a result, NPL series increases in

periods of economic recession and decreases during periods of expansion when there is a recovery of economic activity.

The results are similar across regions. According to Turkey Credit Risk Map based on more than 52 thousand companies operating in twelve different regions in Turkey, the lowest risk is found in Central Anatolia, Western Anatolia, Eastern Marmara, and Istanbul, while Southeastern Anatolia, Northeastern Anatolia, Middle Eastern Anatolia, and the Eastern Black Sea region are defined as high-risk regions. Marmara, Aegean, Mediterranean, and Western Black Sea are regions with moderate risk (Dun & Bradstreet (2012). Apparently, economically and socially developed regions have low credit risk, while economically weak, particularly emigrant regions have higher credit risk (http://ekonomi.haberturk.com/para/haber/792012-en-riskli-il-hangisi).

NPL tends to increase in periods of crises and increased uncertainty. Sharp fluctuations in foreign exchange rates, excessive increases in interest rates, significant declines in foreign exchange reserves, huge increases in the ratio of M2 money supply to international reserves and the ratio of current account deficit to national income (GNP) and increased inflation and unemployment rates are the main indicators of financial crisis. These indicators particularly affect the banking sector, resulting in a greater amount of non-performing loans and a collapse in asset structure due to the real sector shrinkage. Thus, a country with a robust macroeconomic structure has a strong banking sector.

In this study, main macroeconomic variables were selected with possible impact upon NPL. These main macroeconomic variables include the GDP growth rate (Y), inflation rate (P), the ISE-100 Index (MKB), unemployment rate (UR), exchange rate (ER), nominal deposit interest rate (IR), and the percentage changes in M2 money supply (M). Monthly data for the period between 1998.01 and 2012.07 were used for the variables. The NPL value was taken from the monthly bulletins of the Banking Regulation and Supervision Agency and the values for the other variables were obtained from the data distribution systems of Central Bank of the Republic of Turkey and Turkish Statistical Institute (TUIK). The analyses were carried out by EVIEWS 6 software pack.

The established model is as follows.

$$\text{NPL}= \beta_0+ \beta_1\,Y + \beta_2\,P + \beta_3\,\text{MKB} + \beta_4\,\text{UR} + \beta_5\,\text{ER} + \beta_6\,\text{IR} + \beta_7\,M + u \quad (7)$$

Based on model (7), the NPL is expected to decrease with increasing growth rate and ISE index and to increase with increasing interest rate, money supply, unemployment rate, inflation rate, and exchange rate. The Phillips-Perron (PP) test was performed for all variables to test their stationarity. The Engle-Granger(1987) and Gregory- Hansen(1996) methods were employed to detect long-run relations from model estimation and Hendry's General-to-Specific Modeling method was used to detect short-run relations.

3.3. Application

As a first step in the study, stationary of the series is tested by the Phillips-Perron test. The results of the test are shown in Table 1.

Table 1. Results of the PP Test

Variables	Level	First Differences
Y	-2.53	-19.84*
P	-2.44	-6.28 *
ER	-1.99	-11.12*
MKB	-0.63	-14.70*
IR	-2.557	-21.43*
UR	-1.78	-12.74*
M	-2.40	-5.85*
NPL	-1.31	-13.04*

Notes: * Rejection of the unit root hypothesis at the 1% level.

As seen in Table 1, all variables are first-order difference stationary. Thus, residual-based Engle-Granger (1987) method and Gregory-Hansen (1996) method were applied to obtain the long-run static model.

Table 2. The regression results obtained by both Engle and Gregory methods.

ENGLE-GRANGER METHOD				GREGORY-HANSEN METHOD			
Variables	Coefficients	t-statistics	Prob.	Variables	Coefficient	t-statistics	Prob.
Y	-0.182	4.8006	0.000	Y	-0.185	6.122	0.000
P	0.0807	4.318	0.000	P	0.142	8.843	0.000
ER	1.045	11.966	0.000	ER	1.47	19.860	0.000
MKB	-0.211	-12.40	0.000	MKB	-0.185	-13.45	0.000
IR	0.013	1.377	0.170	IR	0.014	1.95	0.052
UR	0.054	0.613	0.540	UR	0.168	2.264	0.024
M	-0.0197	-0.240	0.810	M	0.0304	0.464	0.642
c	-2.116	-1.18	0.239	D1(1999.03)	8.905	9.905	0.000
				c	-10.993	-6.52	0.000
R^2=0.71 F=58.57				R^2=0.818 F=93.33			

In Table 2, the coefficients obtained by the Gregory-Hansen method are close to those obtained by the Engle-Granger method. The result found by the Gregory-Hansen method shows that a 1% increase in growth rate leads to a 0.185% decrease in non-performing loans (NPL), while a 1% increase in the inflation rate increases NPL by 0.142%. A 1% increase in the interest rate increases NPL by 0.014%, while a 1% increase in the unemployment rate increases NPL by 0.168% and a 1% increase in the money supply leads to a 0.0304% increase in NPL. A 1% increase in the ISE index leads to a 0.185% decrease in NPL, while a 1% increase in exchange rate increases NPL by 1.47%. The dummy variable representing the 1999 crisis (D1) has a significant coefficient. All variables except for money supply have significant coefficients. The null hypothesis of a unit root for the residuals from cointegrating regression can be rejected at the 1% significance level. The residual-based tests for cointegration in the presence of a structural break provide stronger evidence in favor of a cointegration between NPL and some macroeconomic variables (i.e., growth rate, ISE index, interest rate, money supply, unemployment rate, inflation rate and exchange rate) for the specific case of Turkey.

In the study, Hendry's General-to-Specific Modeling method was used to detect short-run changes. This is the Autoregressive Distributed Lag Model (ARDL). As it is known, we first need to determine the lag number for the model. SC criterion was used to determine the lag number. The lag number was found to be 1. The General Model estimated using this lag number is shown in Table 3.

Table 3.The General Model

| Variables	Coefficients	t-statistics	Prob.
Y	-0.00895	-0.580	0.562
P	0.0063	1.140	0.255
ER	1.247	1.124	0.262
MKB	0.0265	1.271	0.205
UR	0.114	2.106	0.036
IR	0.000648	0.239	0.811
M	0.0242	1.062	0.298
NPL_{t-1}	0.953	44.48	0.000
Y_{t-1}	0.0013	0.089	0.928
P_{t-1}	0.0043	0.085	0.902
ER_{t-1}	-0.904	-0.783	0.434
MKB_{t-1}	-0.0313	-1.486	0.139
UR_{t-1}	-0.118	-2.156	0.032
IR_{t-1}	0.00392	1.463	0.145
M_{t-1}	-0.0454	-2.022	0.0448
C	-0.174	-0.329	0.742
	R^2=0.98	F=575.33	DW=2.033

Notes: SC=2.62 for k=1; SC=2.77 for k=2; SC=2.92 for k=3; SC=3.04 for k=4; SC=3.20 for k=5.

In Table 3, the General model variables whose coefficients are statistically insignificant and whose coefficients do not meet the economic expectations are excluded. This process was continued until all variables' ccoefficients have probability values smaller than 10% and their signs meet the economic expectations. Table 4 shows the result of the Specific model.

Table 4. The Specific Model

Variables	Coefficients	t-statistics	Prob.
NPL $_{t-1}$	0.974	83.47	0.000
UR $_{t-1}$	-0.108	-2.15	0.033
IR $_{t-1}$	0.0053	2.151	0.032
M$_{t-1}$	-0.045	-2.156	0.032
Y	-0.0158	-1.60	0.10
UR	0.091	1.828	0.069
C	0.308	1.490	0.1308
R^2=0.97 RAMSEY-RESET:0.30	F=1360.164 ARCH(1lag)=0.57 ARCH(2lag)=0.29 ARCH(3lag)=0.24	DW=2.055 F_{LM}(1lag)=0.15 F_{LM}(2lag)=0.13 F_{LM}(3lag)=0.18	

As seen in Table 4, in the short run, a 1% increase in the NPL of the previous period leads to a 0.974% increase in the NPL in period t, while this variable has a higher effect on itself than the other variables. A 1% increase in the unemployment rate in period t increases NPL by 0.091%, while a 1% increase in the unemployment rate for the previous period decreases NPL by 0.108%. A 1% increase in the interest rate for the previous period increases NPL by 0.0053%, while a 1% increase in the growth rate decreases NPL by 0.0158%. All coefficients of the specific model are significant and have high explanatory power. No econometric problems were found in the model. The result of the Ramsey-Reset test also points out the acceptability of the specific model. In other words, the specific model obtained by using restrictions is a good model. Also, the graph of residual for the estimated regression in the period between 1998.01 and 2012.07 is given below.
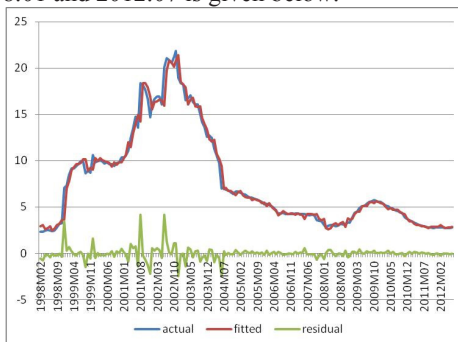
Graph 2. Real and Estimation Values of the NPL Value in the Specific Model

In Graph 2, the real value and estimated value of NPL are compared. Apparently, both values are very close.

4. Conclusion and Evaluation

In this study based on the Credit Portfolio View (CPV) model, by assuming that improved macroeconomic conditions will reduce credit risks, the macroeconomic variables with possible impact on credit risks were identified and an econometric model was established. In the formulated econometric model, "the ratio of non-performing loans to total loans" (NPL) was used to represent credit risks. The independent variables employed include inflation rate, interest rate, the ISE-100 index, exchange rate, growth rate, percentage changes in M2 money supply, and unemployment rate. Monthly data for the period between 1998.01 and 2012.07 were used. The General-to-Specific Modeling method developed by Hendry (1980) was used to analyze short-run dynamic relations between credit risk and macroeconomic factors, while the methods developed by Engle-Granger(1987) and Gregory-Hansen (1996) were employed to analyze long-run relations.

Both methods suggest that an increase in the ISE index and growth rate leads to decline in banks' credit risks. An increase in money supply, exchange rate, unemployment rate, inflation rate, and interest rate, on the other hand, increase banks' credit risks. The result of the specific model demonstrates that the previous period's credit risk has a significant impact on the current period's credit risk. An increase in the interest rate and unemployment rate in the previous period leads to increases in banks' credit risks.

As it is well known, with the letter of intent presented to the IMF on December 9, 1999, Turkey started to implement a three-year stabilization program aimed to "reduce inflation, lower real interest rates to reasonable levels, enhance the prospects of growth, and provide a more effective and fair allocation of the resources". Monitoring the course of the stabilization program using certain macroeconomic indicators reveals that the growth and inflation rates were highly unstable, the interest rates reached significant levels, the Turkish Lira rose in value with the fixed exchange rate system, there was a decline in the ISE index, which is a main indicator of the changes in the prices of securities in the economy, and the money supply increased. Before the end of the first year of the stabilization program, the financial crises of November 2000 and February 2001 took place. Particularly in relation to our subject, the default rates for bank loans rose from 7.2% in 1998 to 10.5% in 1999 and up to 28.6% in 2001 after the crisis and to 24.4% in 2002 (Yay, 2004:17). Following the 2001 crisis, Turkey's economy grew and there was a decline in the default rates for bank loans in this conjuncture. Although there was an increase in this rate with the 2008 crisis, it started to decline after 2010. Thus, there is a decrease in banks' credit risks in periods of economic expansion –when there is an improvement in macroeconomic indicators-, while credit risks increase in periods of crisis and recession. This study also supports this argument. As a conclusion, it is argued that banks' credit risks are affected by macroeconomic factors and an economically robust conjunctural environment in Turkey will not create any problems for banks' credit risks.

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