

USING NON-PERFORMING LOAN RATIOS AS DEFAULT RATES IN THE ESTIMATION OF CREDIT LOSSES AND MACROECONOMIC CREDIT RISK STRESS TESTING: A CASE FROM TURKEY

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Abstract

In this study, inspired by the Credit Portfolio View approach, we intend to develop an econometric credit risk model to estimate credit loss distributions of Turkish Banking System under baseline and stress macro scenarios, by substituting default rates with non-performing loan (NPL) ratios. Since customer number based historical default rates are not available for the whole Turkish banking system's credit portfolio, we used NPL ratios as dependent variable instead of default rates, a common practice for many countries where historical default rates are not available. Although, there are many problems in using NPL ratios as default rates such as underestimating portfolio losses as a result of totally non-homogeneous total credit portfolios and transferring non-performing loans to asset management companies from banks' balance sheets, our aim is to underline and limit some ignored problems using accounting based NPL ratios as default rates in macroeconomic credit risk modeling. Developed models confirm the strong statistical relationship between systematic component of credit risk and macroeconomic variables in Turkey. Stress test results also are compatible with the past experiences.

Keywords: Credit Risk, Credit Portfolio View, Macroeconomic Stress Testing, Non Performing Loan Ratios, Turkish Banking System

1. INTRODUCTION

Due to national, regional and global scale financial crises that have become highly frequent since 1990s as a result of globalization, financial liberalization, poor macro-and-micro governance and inadequate regulation and supervision and, experienced difficulties in establishing and maintaining the financial stability, detecting and analyzing the vulnerabilities of financial systems are becoming very crucial for countries and international institutions that pursue the financial stability. The main tools used for testing the financial strength and detecting the potential vulnerabilities of the financial systems are macroeconomic stress tests.

Indeed, as a result of Financial System Assessment Programs (FSAP) that have carried out by the IMF and World Bank after the 1997-98 East Asian financial crises, macroeconomic stress testing of countries' financial systems across all around the world have become a common practice.

The direction and the magnitude of the statistical relationship, known to exist, between macroeconomic variables and the systematic component of credit risk provides invaluable opportunities to the regulatory and supervisory institutions and other authorities responsible for financial stability, to assess the likely effects of the

credit risk -which is the most important of all the risks that financial sector bears- under different macroeconomic conditions and stress levels.

Today most of the developed countries' central banks and/or supervisory authorities have their own macroeconomic credit risk models for stress testing of their financial systems (Foglia, 2009:34-42).

In fact, macroeconomic credit risk portfolio model CreditPortfolioView (CPV), developed by Wilson (1997a and 1997b) for commercial purposes has had a huge effect on the macro econometric models that have developed later on for credit risk stress testing purposes. CPV approach have adopted in various ways for the banking sectors of many countries (See Boss, 2002; Virolainen, 2004; Küçüközmen and Yüksel, 2006; Wong, Choi and Fong, 2006; Fong and Wong, 2008; Otani, Shiratsuka, Tsurui and Yamada, 2009; Avouyi-Dovi, Jarret, Kendaoui, Moquet Jeremy and Bardos, 2009; Kattai, 2010).

However modeling the credit risk is not an easy task. Most crucial data for a healthy macro econometric credit risk model is properly calculated historical default rates with sectoral and credit quality breakdowns. But it is very well known that total number of central bank and supervisory authority that might have such data for their entire banking system is less then very few.

When the historical default rates are unavailable, for econometric modeling of credit risk, the best option left is to use accounting based non-performing or loan loss ratios as dependent variable which has to be explained by independent macro variables (See Kalirai and Scheicher, 2002; Jimenez and Saurina, 2005; Baboucek and Jancar, 2005; Küçüközmen and Yüksel, 2006; Wong et al., 2006; Jakubik, 2007; Glogowski, 2008; Fong and Wong, 2008; Kattai, 2010).

In this study, encouraged by the CPV approach and later studies that adopted this approach for credit risk stress testing purposes, we tried to develop an econometric credit risk model to estimate credit loss distributions of Turkish Banking System under baseline and stress macro scenarios, by substituting default rates with non-performing loan (NPL) ratios. However there are many problems in using NPL ratios as default rates such as underestimating portfolio losses as a result of totally non-homogeneous total credit portfolios and transferring non-performing loans to asset management companies from banks' balance sheets. It is also possible to come across diametrically opposite results with regard to the effects of macro variables on defaults. We attempted to address or limit some of these problems.

The composition of the paper is as follows: Next section is devoted to credit risk modeling. It begins with a quick review of credit risk components and their relations with credit risk capital and provisions. It goes on with the problem areas of credit loss distributions, default rates and non-performing loan ratios. Macroeconomic modeling of credit risk and portfolio models' approaches to systematic component of credit risk are also touched in this section. Section III explains CPV approach for macroeconomic stress testing and empirical literature. Section IV introduces the empirical model that is developed for Turkish banking system. Simulation and stress testing of portfolio losses are explained in Section V and VI. Section VII presents summary and concluding remarks.

2. MODELING OF CREDIT RISK

In short, credit risk can be defined as the risk of loss that a lender could face either due to debtor's default on contractual payments or due to increases in the default probability of debtor's as a result of downgrading etc. Therefore credit risk can be modeled in two broad modes. Default only mode and mark to market mode. Mark to market mode covers losses that is originated both from default and credit quality migrations. In this study we will cover only default mode of credit risk modeling since it is probably more than enough for the banking systems of most countries where even historical default rates are not available let alone credit quality migration likelihoods.

2.1. General Framework

Credit risk measurement is based upon the estimation of expected and unexpected losses. In the credit risk literature, for a single credit transaction (i) or for a credit portfolio (p), credit risk generally is unfolded with the below equations (See ; Ranson,

2003; Ong, 2005; Colquitt, 2007; Van Gestel and Baensens, 2009)²

$$\text{Credit VaR} = \text{EL} + \text{UL} \quad (1)$$

$$\text{EL}_i = \text{PD}_i * \text{EAD}_i * \text{LGD}_i \quad (2)$$

$$\text{EL}_n = \sum_i^j \text{EL}_i = \sum_i^j \text{PD}_i * \text{LGD}_i * \text{EAD}_i \quad (3)$$

$$\text{UL}_i = \text{EAD}_i * \sqrt{[\text{PD}_i * (1 - \text{PD}_i) * \text{LGD}_i^2 + (\text{PD}_i * \sigma_{\text{LGD}_i}^2)]} \quad (4)$$

$$\text{UL}_i = \text{EAD}_i * \sqrt{[(\text{PD}_i * \sigma_{\text{LGD}_i}^2) + (\text{LGD}_i^2 * \sigma_{\text{PD}_i}^2)]} \quad (5)$$

$$\text{UL}_p = \sqrt{[(\text{UL}_i^2 + \text{UL}_j^2) + (2\rho_{ij} * \text{UL}_i * \text{UL}_j)]} \quad (6)$$

Where Credit VaR=Credit Value at Risk; EL=Expected Loss; UL=Unexpected Loss; PD=Probability of Default; EAD=Exposure at Default; LGD=Loss Given Default Rate; (σ) = standard deviation; (ρ)=correlation coefficient.

As it can be understood from above equations, credit risk calculations consist of estimating (i) the default probability of each borrower for a certain future period of time and its likely deviations from the average (ii) the probable total amount of money (principal, interest etc..) that borrowers would be in debt at the time of the default in the future (iii) the probable percentage of non recoverable amount (1-recovery rate) and its deviations, according to credit quality of borrowers and type of collaterals (iv) default correlations among individual borrowers.

EL is the average credit loss that one can expect from a single credit transaction or a portfolio. It is accepted as the cost of credit, the most important variable of risk based credit pricing. For a single credit transaction it can be calculated simply by multiplying PD, EAD and LGD. For a portfolio it is simply the sum of expected losses of single transactions. Diversification of credit risk has no effect on portfolio EL.

UL is the estimated statistical volatility of EL. Portfolio UL is less than the sum of unexpected losses of single credit transaction as long as the default correlation coefficient among credit borrowers is less than +1. Portfolio diversification effect increases when the default correlation coefficients become closer to -1.

UL has to be calculated by parametrically or separated from Credit VaR loss distribution, generated by Monte Carlo simulations, with a certain probability of confidence level. Credit VaR is the basic statistical methodology for measuring credit risk over the banks' credit portfolios with thousands customers. Unlike market risk VaR distributions, Credit VaR distribution consist of both EL and UL, because expected mean or median of the distribution always positive. When the EL is separated from the Credit VaR by using mean or median of the total loss distribution, the remaining part is to be equal to the UL.

²The equations for EL and UL, more or less, can be found exactly in the same form in many sources though it is possible to come across with small variations depending upon the assumptions with regard to the some basics such as the correlation level between PD and LGD. Using EDF (Exposure Default Frequency) notion instead of PD (Probability of Default) is also highly common. Again, intensity approaches of default use different notions such as 'default intensity' and 'hazard rates' (See. Duffie and Singleton, 2003:59-72). For the derivations of EL and UL equations see Ong, 2005:101-103, 116-118, and 132-133.

In theory, including Basel II's internal rating based but Merton-like credit risk functions (BCBS, 2004), minimum level of bank's economic capital and provision obligations for credit risk are also determined by the EL and UL.

$$\text{Credit Provisions} \geq \text{EL} \quad (7)$$

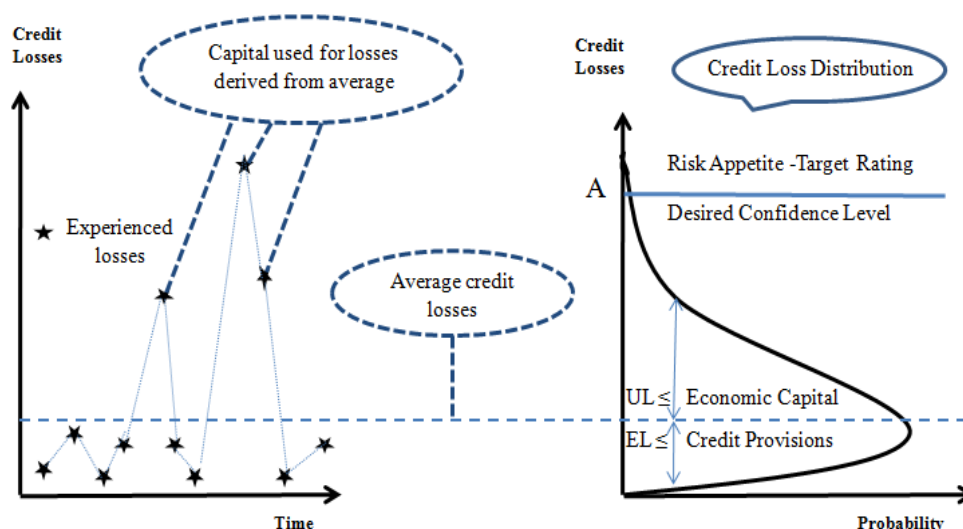
$$\text{Economic Capital} \geq (\text{Credit VaR-EL}) \text{ or UL} \quad (8)$$

Since EL is considered as the cost of credit or cost of doing job, it must be debited to the profit and loss accounts via provisions or deducted from capital in advance. Economic capital which is also known as risk capital or risk-based capital is the

amount of capital needed to protect banks against financial shocks in the event of unexpectedly large losses. Actually it is a buffer to absorb such losses (Bhatia, 2009:1). Economic capital is required to cover unexpected losses with a certain probability of confidence level. Since each bank has different risk appetite, which means different target rating and different target return on equity, they may desire to operate with different confidence level of economic capital as long as they meet the minimum regulatory requirements.

The relationship between bank's capital and provisions and credit losses can be illustrated as it is seen in Figure 1.

Figure 1. Economic Capital and Provisions for Credit Risk



Source: Kuo (2008)

2.2. Problems with Credit Loss Distribution

Though, in the literature EL and UL are, generally, symbolized by mean (μ) and with its standard deviation (σ) successively, every parametric calculation that is made without knowing the statistical shape of the loss distribution might be misleading. For instance, if EL is known, UL can be calculated easily by using EL's standard deviation with different confidence levels under normal distribution assumption. However in the real world, normal distribution of credit losses could hardly be seen.

Empirical findings suggest that credit loss distributions are highly skew and peak, as can be seen on right side of Figure 1. For instance in the cumulative standard normal distribution, for reaching %99,99 confidence level, it would be enough to move 3,71 standard deviation to the right of the mean or median. However it is very well known that in many commercial banks to cover the tail loss events in the credit portfolio loss distributions, it is necessary to move 6 and 8 standard deviation from the mean (Ranson, 2003:182).

Though skewness of credit loss distribution can be explain, partially, with the fact that credit losses cannot take negative values, hence expected mean or median of the distribution is positive, main reason for extreme skewness should be non-

homogeneity. Since huge amount of the total credits extended by the banks goes to a very small number of the total credit customers, most of the default events actually occur within small amount credits. But for the same reason, tail events can cause huge losses.

An important problem that has to be solved for highly skewed credit loss distributions is to chose correct measure of central tendency to separate EL from Credit VaR. When the distribution is normal, using mean or median does not make any difference since both are equal or near equal. However in a skewed distribution median is smaller than the mean because it is less affected by outliers and skewed data. Hence, choosing mean as the measure of central tendency can exacerbate EL while underestimating UL.

In fact, empirical findings revealed that this problem also exists in credit rating statistics. It is known that average default rates calculated for rating notches exceeds median of the distribution and this may be causing mistakes in calculating EL and credit pricing (Crouhy, Galai and Mark, 2000:85).

2.3. Problems with Default Rates and NPL Ratios

Unquestionably PD is the most crucial component of credit risk. PD can be produced mainly (i) from historical default rates based on external or internal credit ratings statistics, (ii) from Merton type credit

models based on market equity prices, (iii) from reduced form models based on credit risk spreads. For a macro econometric modeling of credit risk for the entire banking system, first option is the most convenient.

On the other hand, historical default rates can be calculated mainly on two different bases: (i) default incidence or defaulted customer number based (ii) defaulted exposure or monetary value based. (Colquitt, 2007:229). Though, in some studies, bankruptcy statistics are used to calculate default incidence based rates, every default may not lead bankruptcy. On the other hand, exposure based default rates could be misleading because of non-homogeneity if they are used as PD in Monte Carlo simulations to generate total credit loss distribution, which requires to know at least monetary value of each credit and total number of credit customers or files in the actual credit portfolio.

When the historical defaults rates are not available, practically the best option is to use accounting based ratios as a substitute of monetary value based default rates. Basically, there are two accounting based ratios for a simple and rough approximation for default or expected loss rates: (i) Non Performing Loans/ Tota Loans (ii) Credit Loss Provisions/Total Loans. In the first ratio nominator is the approximation of PD*EAD, denominator is the approximation of EAD and result is the approximation of the PD. In the second ratio nominator is the approximation of PD*EAD*LGD, denominator is the approximation of EAD and result is the approximation of the PD*LGD or EL rate. The ratio of Credit Loss Provisions to Non Performing Loans, also can be used as the approximation of LGD, though great care is needed.

Besides, while using NPL ratios as default rates, extra caution have to be given for their interpretation. For instance, normally, it is expected that sharp devaluation of domestic currency has negative effect on default rates, in other words, make them higher. But when it comes to the NPL ratios, a different picture may arise. Because of foreign currency nominated loans, at the outset, denominator might increase sharply while depressing NPL ratios considerably below. Hence working with the lags of macro variables becomes much more important when using accounting based information in macroeconomic modeling of credit risk.

Another problem with regard to the accounting based problem loan ratios is their openness for treatment. Non-performing loan rates are affected from every debit and credit to nominator and denominator of the ratio. Bu the most important of all is the selling of problem loans to third parties, e.g. asset management companies, for collections, which causes removing problem loans and their provision from the balance sheets.

An additional problem is the inclusion of off-balance sheet credits to the analysis, because the origin of the non performing loans is generally not known or classified.

2.4. Macroeconomic Modeling and Portfolio Models' Approaches

Credit risk factors which triggers default events can be sum up under two broad categories by using a borrowed concept from Modern Portfolio Theory: (i) Systematic risk factors (ii) Specific risk factors. Systematic risk factors, more or less, affect all

borrowers while specific risk factors unique to a individual borrower or transaction.

Strong relationship between macroeconomic variables and systematic component of credit risk is very well known and supported by empirical findings. Indeed, macro variables affect not only PD, but also LGD, since recovery rates are affected by macro conditions as well (See Allen and Saunders, 2003).

Explaining 'systematic' component of credit risk by independent macro variables and attaching random error term to the 'specific' or 'idiosyncratic' component of credit risk is the basic idea behind econometric credit risk models, including portfolio model CPV.

Actually all well-known credit portfolio models, namely KMV's Portfolio Manager, JP Morgan's Credit Metrics, Credit Suisse Financial Products' CreditRisk + and Wilson's CPV, try to link default and/or credit quality migration correlations to the systematic credit risk factors with different ways and scales.

But, as revealed by Koyluoglu and Hickman (2005), portfolio models have many common postulations. For instance the correlation structure of defaults can be attributed to the dependence of obligors to the same systematic factors and, if idiosyncratic components are independent across all obligors, then the conditional default behavior becomes independent. Conditional loss distributions, for a given macroeconomic condition, could be generated by using independent defaults, an assumed LGD and EAD. However aggregation of conditional loss distributions by using respective probability distribution for systematic factors, gives unconditional loss distribution of the portfolios.

3. CPV APPROACH FOR MACROECONOMIC STRESS TESTING AND EMPIRICAL LITERATURE

The basic idea of Wilson's CPV is to link default rates and credit quality migrations to macroeconomic variables. Model can be used either in default only mode or mark to market mode. Since CPV has not publicly available technical document such as Credit Metrics or Credit Risk+, details of the model could be drawn from the explanations made in Wilson (1997a, 1997b and 1998).

The default only mode of CPV approach has four steps: (i) establishing an econometric equation to link average default rates to some macro variables (ii) establishing an econometric equation set for macro variables for their future evolutions (iii) contracting the correlation structure of model (iv) simulating new values for macro variables and average default rates and generating portfolio loss distribution.

In the first step, the average default rate for each sector is modeled by the logistic functional form which ensures that the default rates estimates are in the range [0,1] and their relation with macro variables are not linear (as we will see, parameters of the $y_{j,t}$ are estimated by means of linear regression) as

$$p_{j,t} = \frac{1}{1 + \exp(y_{j,t})} \quad (9)$$

Where $p_{j,t}$ is the default rate in sector j at time t, and $y_{j,t}$ is the sector specific macroeconomic index that a higher value for implies a better state of the economy with a lower default rate $p_{j,t}$, and vice versa.

From equation (9), the value of macro index given default rate is calculated as:

$$y_{j,t} = \ln \left(\frac{1 - p_{j,t}}{p_{j,t}} \right) \quad (10)$$

In order to find the empirical link to macro variables, macroeconomic index (the logit transformed default rates) is assumed to be determined by a number of exogenous macroeconomic variables, i.e.:

$$y_{j,t} = \beta_{j,0} + \beta_{j,1}X_{1,t} + \beta_{j,2}X_{2,t} + \dots + \beta_{j,n}X_{n,t} + u_{j,t} \quad (11)$$

Where $y_{j,t}$ is macroeconomic index value for sector j at time t , $\beta_j = (\beta_{j,0}, \beta_{j,1}, \beta_{j,2}, \dots, \beta_{j,n})$ is a set of regression coefficients to be estimated for the sector j , $X_{j,t} = (X_{j,1,t}, X_{j,2,t}, X_{j,3,t}, \dots, X_{j,n,t})$ is the set of explanatory macroeconomic variables (GDP, interest rates, unemployment rates, etc.) and $u_{j,t}$ is a random error that covers 'idiosyncratic' component of credit risk, assumed to be independent and identically normally distributed.

The second step is to model evolution of individual macroeconomic variables. To add a dynamic component to the model, Wilson assumes that each of the macroeconomic variables follows a univariate autoregressive of order two (AR(2) process)

$$X_{i,t} = k_{i,0} + k_{i,1}X_{i,t-1} + k_{i,2}X_{i,t-2} + \varepsilon_{i,t} \quad (12)$$

Where k_i is a set of regression coefficients to be estimated for the i^{th} macroeconomic variable, and $\varepsilon_{i,t}$ is a random error that covers the impact of outside factors, assumed to be independent and identically normally distributed.

The third step is the construction of correlation structure. Equation (11) and equation (12) define a system of equations governing the joint evolution of the default rates and associated macroeconomic variables. The system has a $(J + 1) \times 1$ vector of error terms, or innovations, E , and a $(J + 1) \times (J + 1)$ variance-covariance matrix of errors, Σ , defined by:

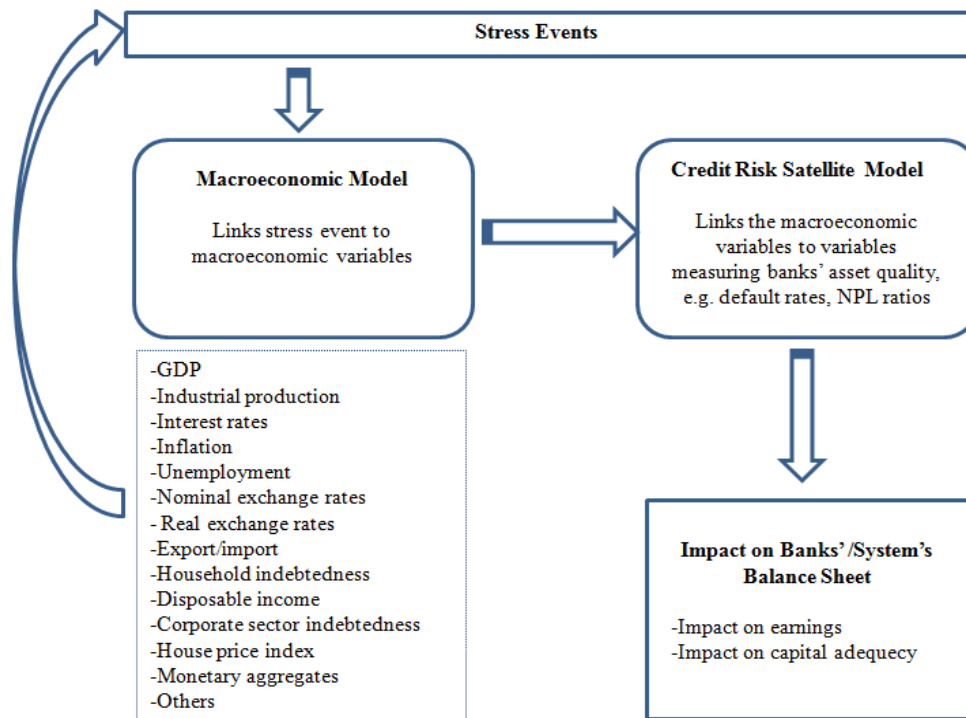
$$E = \begin{pmatrix} u \\ \varepsilon \end{pmatrix} \sim N(0, \Sigma), \quad \Sigma = \begin{bmatrix} \Sigma_u & \Sigma_{u,\varepsilon} \\ \Sigma_{\varepsilon,u} & \Sigma_\varepsilon \end{bmatrix} \quad (13)$$

As stated in Boss (2002), the covariance matrix models the interdependence of shocks in the macroeconomic variables and their impact on the macroeconomic index. This approach is based on the notion that an oil price shock, for instance, also has a negative impact on industrial production and on other macroeconomic variables.

The final step is the simulation of default rates' future paths and portfolio loss distributions by Monte Carlo method. If A is accepted as the Cholesky matrix which will provide $\Sigma = AA^T$ equalization, future paths of variables in the equation system might be simulated by drawing random numbers, for vector E , from standard normal distribution and correlating them by A^T , Cholesky transpose. By assuming that defaults are independent conditional on the state of the economy as stated by the macroeconomic variables included in the model, it is then possible to generate credit loss distributions.

To give an idea about the usefulness of the CPV approach, an illustration of typical macroeconomic stress testing framework for credit risk is given in Figure 2. For an intensive review of financial system stress testing practices and literature, interested readers are advised to consult Rosch and Scheule (2008) and Quagliariello (2009).

Figure 2. General Framework for Macroeconomic Stress Testing of Credit Portfolios



Source: Cihak (2007) and Foglia (2009)

When we consider CPV within the framework, equation 11 is a satellite credit risk model that links macro variables to default rates while equation 12 is a macroeconomic model that links innovations (shocks) to macro variables. After generating credit loss distribution for a baseline macroeconomic scenario it is easy to manipulate macro scenarios (innovations) and analyze likely effects on earnings (provisions) and capital adequacy of the banking systems simply by calculating EL and UL under different scenarios and different level of confidence (see equations 7 and 8).

Because of its perfect fit, Wilson's CPV approach has been adopted in various ways for macroeconomic credit risk stress testing purposes. Early adaptations of Boss (2002) and Virolainen (2004) also have become a main reference source for later studies.

Boss (2002) implemented CPV for Austria's banking system. Using least square method (LSM), he estimated four satellite model for different sectors (corporate, household etc.). The rate of bankrupted firms to total firms was used as default rates. AR 2 process was used for macroeconomic variables as suggested by Wilson. In portfolio loss simulations LGD was assumed 30%.

Virolainen (2004) adapted CPV for six economic sectors with Finnish data. Default rates were calculated from bankruptcy statistics. Satellites estimated by seemingly unrelated regression (SUR). Macroeconomic variables modeled by using AR 2 process. LGD was assumed 50%.

In Wong et al. (2006) CPV adapted for Hong Kong banking system. All equations were estimated with SUR method. Second application for Hong Kong was made by Fong and Wong (2008). In this study mixture Vector Auto Regressive (Mixture VAR) method is used for all variables. Non-performing loan ratios were used as default rates in both studies.

For the Turkish corporate loan portfolio, CPV was adapted by Küçüközmen and Yüksel (2006). They used non-performing loan ratios for corporate loan portfolio of the sector with industry breakdowns. Satellites were estimated by LSM, while macro variables were modeled using by autoregressive integrated moving average (ARIMA) structures.

Otani et al. (2009) used CPV to relate credit quality migrations likelihoods with macro variables for Japan banking system. For macroeconomic model, vector auto regressive (VAR) method was preferred.

In Avouyi-Dovi et al. (2009) CPV was adapted for French manufacturing industry by using historical default rates with credit quality breakdowns. They used only one VAR model for both default rates and macro variables.

In Kattai (2010), sectoral non-performing loan ratios, after some accounting based adjustments, were used as default rates for Estonian banking system. In the satellite models macro variables generally were used with their lagged values. VAR method was chosen for modeling macro variables.

4. EMPIRICAL MODEL

As historical defaults rates are not available for whole banking system and rough credit amount

distributions are only available for the total cash credit portfolio without sectoral breakdowns we will attempt to develop only one satellite credit risk model for the total on-balance sheet loan portfolio of the Turkish Banking System by substituting default rates with NPL ratios. We are not able to make any alterations on the NPL data for non cash credits since the origins are not classified.

4.1. Data

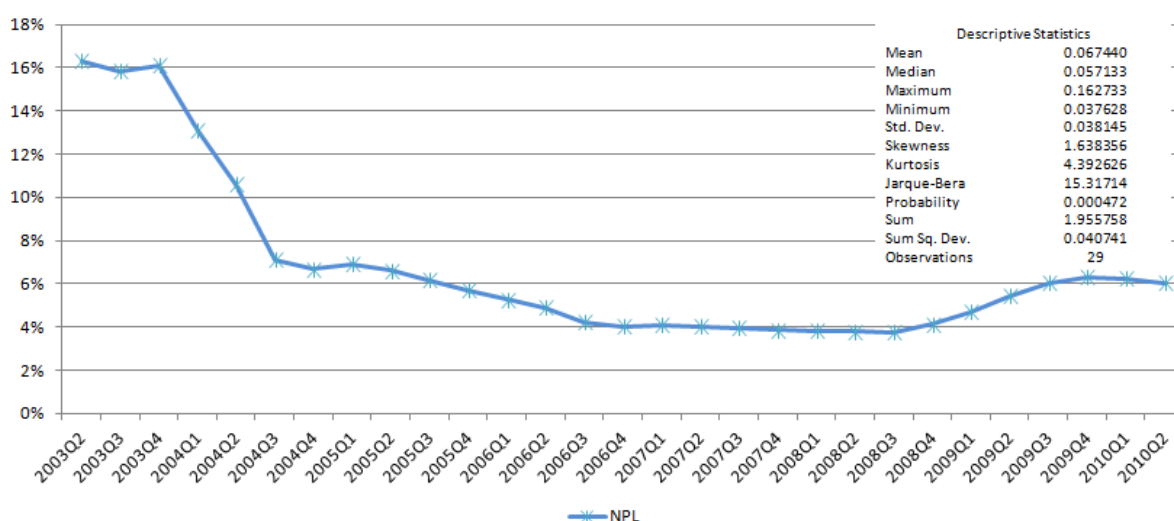
In this study NPL ratios are used as dependent variable after logistic transformation. NPL ratios are calculated, from Banking Regulation and Supervision (BRSA)'s publicly available data sets, for each quarter, starting from 2003Q1 to 2010Q2, as dividing total non-performing loans at time t_1 by the normal performing loan portfolio at time t_0 , by using their three month averages within the quarter. 90 days lag between nominator and denominator is given with the assumption that at least three-month period is necessary before declaring a loan as non-performing or defaulted. The data which belongs before 2003 is excluded from the analysis as the banking system faced with huge financial crises in 2000 and 2001 and later went into an intense recapitalization process.

Before calculating NPL ratios data set is corrected for non-performing loans that is transferred to asset management companies widely starting from 2008Q1. As of 2010Q2 total value of re-added non-performing loans to the nominator of the ratio has reached 3,4 billion Turkish Liras (TL), 16% of the total non-performing portfolio.

As it can be followed from Figure 3, NPL ratios of the banking system, after recapitalization and economic recovery, were reduced gradually from 2003Q4 to 2008Q2, however after sub-prime crises, as a result of severe economic recession they began to increase from 2008Q3 and starting from the first quarter of 2010 with the economic recovery they began to decrease again. Their strong correlation with the general macroeconomic condition looks like obvious.

In the study, macro factors that are tested as independent variables are gross domestic product (GDP), nominal interest rates, ex-ante reel interest rates, ex-post reel interest rates, Consumer Price Index (CPI) inflation rates, Wholesale Price Index (WPI) inflation rates, USD/TL exchange rates, EURO/TL exchange rates, currency basket/TL rates, CPI reel exchange rate index, WPI reel exchange rate index, total unemployment rates, rural unemployment rates, urban unemployment rates, monetary aggregations (M1, M2 and M3), domestic consumption, capacity utilization rates and industrial production index. All of the macro data except GDP and domestic consumption are available in monthly periods or more frequent. GDP and domestic consumption data is available quarterly. Hence we used quarterly averages of other macro variables starting from 2003Q1 to 2010Q2. Except interest rates all macro data is obtained from Central Bank of Turkey or Turkish Statistical Institute. Interest rate data for secondary market of treasuries is obtained from market information providers.

Figure 3. Non Performing Loan Ratios



4.2. Satellite Credit Risk Model

In the first step, by using equation 10, NPL ratios (NPL) were transformed logarithmically to a macroeconomic index (INDEX) variable. Later we checked correlation coefficients between INDEX and all macro variables up to four time lags. In the end we choose four prospective macro variables which we think they are more suitable to define different macro scenarios and cover different aspect of credit risk. Macro variables that are chosen as potential independent variables are GDP, nominal interest rates (IR), USD/TL exchange rates (USD) and CPI inflation rates (CPI).

As it is expected, correlation between GDP and INDEX is strongly positive for all levels, which means GDP and NPL correlation is strongly negative. Correlation between INDEX and IR is weakly positive at the level, however at the first lag it turns negative and sharply increases as the time passes. It implies that in the early stages higher interest rates can boost economic growth as a result of capital inflows, a very well-known phenomenon for emerging market economies. Hence it is normal to see negative effects of interest rates on INDEX at the later stages. USD-INDEX correlation is mildly negative and highly stable at the time lags. It is not contrary to the expectations. Correlation structure between CPI and INDEX is very similar to the correlation structure of IR and INDEX as a result of very high positive correlation between CPI and IR variables. Because of its complicated nature and side effects, we are not imposing any expectation with regard to the sign of the correlation between CPI and INDEX or NPL. However our intention is to use CPI as a counter variable to IR and USD to display their reel effects on the dependent variable. Along with chosen macro variables, NPL also will be used as independent variable with its one or two lagged values to feed the model back.

Graphical tests for seasonality show that, non-surprisingly, GDP variable has seasonal trend. For removing seasonality CensusX12 additive method is used. Newly generated GDP_SA variable is free from seasonality. However Augmented Dickey-Fuller (ADF) Test which we used for unit roots is proved GDP_SA as non-stationary. Differencing is used for stationary. Regenerated DGDP_SA variable is

stationary. ADF Test results for unit roots are presented in table 1.

Table 1. Augmented Dickey-Fuller Test Statistics

Variables	Model	t-Statistic	Probability	Critical Values	Result
INDEX	Intercept	-4.0102	0.005	-3.7114(1%)	Stationary
NPL	Intercept	-3.5584	0.0146	-2.9862(5%)	Stationary
GDP_SA	Intercept and trend	-2.1214	0.4684	-3.2253(10%)	Non stationary
DGDP_SA	Intercept	-3.7879	0.0079	-3.6891(1%)	Stationary
USD	Intercept	-2.6794	0.0897	-2.6229(10%)	Stationary
IR	Intercept and trend	-5.2131	0.0012	-4.3239(1%)	Stationary
CPI	Intercept and trend	-4.3738	0.0096	-4.3560(1%)	Stationary

Satellite model is estimated by LSM. INDEX is dependent variable. At the outset, all potential explanatory macro variables are included in the model with their level and 1, 2, 3 and 4 lagged values. As long as they take logical signs with significant t-statistic and low probability and do not cause any problems for other statistical tests we keep them in the model. Because we think in a dynamic model, the aim of which is to estimate future paths of variables in a continuous manner, even contradictory impacts on the dependent variable at the different time lags has to be taken into consideration as long as a meaningful explanation does exist. The selected regression equation for dependent variable is given in table 2.

Table 2. Regression Results for Macroeconomic Index

Variables	Co-efficient	Standard Error	t-Statistic	Probability
DGDP_SA(-1)	4.44E-08	1.80E-08	2.467094	0.0253
DGDP_SA(-2)	7.56E-08	2.03E-08	3.730324	0.0018
DGDP_SA(-3)	9.07E-08	2.43E-08	3.731277	0.0018
IR	2.225097	0.330344	6.735687	0.0000
IR(-3)	-1.724885	0.272703	-6.325148	0.0000
CPI	-4.316774	0.822643	-5.247447	0.0001
CPI(-3)	3.435437	0.612964	5.604631	0.0000
USD(-2)	-0.672526	0.117099	-5.743220	0.0000
NPL(-2)	-10.78733	0.731479	-14.74728	0.0000
Constant	4.439319	0.217168	20.44190	0.0000
R-squared	0.989237		S.E. of regression:	0.044336
Adjusted R-squared	0.983183	F-statistic	163.4022	

Coefficient signs of all DGDP_SA lags are positive which means economic growth may reduce NPL ratios. Coefficient signs of IR imply a boosting effect on the economic growth at the first stage but later its effect turns negative. IR and CPI take opposite signs in both level and in their lagged values which we consider as normal. Negative coefficient signs for USD and NPL lags imply that increases in foreign exchange rates and default events reduce the performance of the economy as expected.

Durbin Watson statistics, Correlogram-Q Statistics and Breusch-Godfrey Serial Correlation LM test confirm that residuals do not contain autocorrelation. Jarque-Bera statistics and histogram show that residuals are normally distributed. Finally, White test proves no-heteroskedasticity while high F and t statistics demonstrate that there is no collinearity problem between variables.

4.3. Macroeconomic Model

For modeling macro variables we will use a vector autoregressive (VAR) model as preferred in Otani et al. (2009) or Kattai (2010). VAR model, made popular by Sims (1980) has proven to be especially useful for describing the dynamic behavior of economic and financial time series and for forecasting. Flexible and easy to use nature of the method makes vector autoregression attractive for modeling of multivariate time series. By using VAR we will have an equation for each macroeconomic variable. Actually, each equation of the VAR model can be estimated by LSM if we use exactly the same variables, but coefficients in the equations may look like insignificant or irrelevant. However when we combine them in a VAR model, then as a whole, they can be found significant and relevant, for example by using standard F statistics (Gujarati, 1999).

For choosing lag structure of the VAR model, we are using lag order selection criterion (Akaike, Schwarz, Hannan-Quinn etc.). Most of the criterion suggest a VAR(2) model, estimation results of which are given in Table 3.

Table 3. VAR(2) Model Estimation Results

Variables	DGDP_SA*	IR*	CIP*	USD*
DGDP_SA(-1)	-0.025553 (0.22575)	1.05E-08 (8.3E-09)	7.46E-09 (5.0E-09)	-3.27E-09 (3.8E-08)
DGDP_SA(-2)	0.294213 (0.19230)	8.35E-10 (7.1E-09)	4.35E-09 (4.3E-09)	-6.33E-08 (3.2E-08)
IR(-1)	-4271823. (4673807)	1.145056 (0.17237)	0.103816 (0.10407)	0.380923 (0.78000)
IR(-2)	3089971. (4834289)	-0.573149 (0.17829)	-0.048012 (0.10765)	-1.321957 (0.80679)
CIP(-1)	-5828726. (7578748)	-0.386688 (0.27951)	0.875771 (0.16876)	1.452551 (1.26481)
CIP(-2)	4198845. (7089558)	0.631292 (0.26147)	-0.275124 (0.15787)	0.729530 (1.18317)
USD(-1)	-109132.6 (1401047)	-0.082893 (0.05167)	-0.012143 (0.03120)	0.655814 (0.23382)
USD(-2)	2666545. (1565776)	-0.023496 (0.05775)	-0.021125 (0.03487)	0.004829 (0.26131)
Constant	-3067102. (1653736)	0.193496 (0.06099)	0.071393 (0.03682)	0.463344 (0.27599)
R-squared	0.466521	0.913251	0.877887	0.644219
Adj R-squared	0.229419	0.874695	0.823614	0.486094
S.E. of equations	508619.6	0.018758	0.011326	0.084883
F-statistic	1.967595	23.68678	16.17553	4.074117

Note: *Standard errors of coefficients are presented in parentheses

For 27 observations and 9 degrees of freedom, we find F-statistics satisfactory. We check model for normal distribution, autocorrelation, heteroskedasticity and stability. Model passes all tests with high satisfaction. We find nothing against the fact that random errors terms (residuals) of the equations follow a white noise process.

4.4. Correlation Structure of Entire Model

Correlation matrix of VAR and satellite model residuals is provided in Table 4. Correlation signs prove the consistency of entire model.

Table 4. Residual Correlation Matrix

	DGDP_SA	IR	CIP	USD	INDEX
DGDP_SA	1.000000	-0.054423	0.083502	-0.398035	0.244818
IR	-0.054423	1.000000	-0.200869	0.172115	-0.114824
CIP	0.083502	-0.200869	1.000000	0.054237	0.012487
USD	-0.398035	0.172115	0.054237	1.000000	-0.369512
INDEX	0.244818	-0.114824	0.012487	-0.369512	1.000000

5. MONTE CARLO SIMULATIONS

In this step, we will run two Monte Carlo simulations. First simulation is for future values of INDEX and NPL ratios under stochastic baseline macro scenario. Second simulation is for estimating credit loss distributions under given NPL or default rates. However before using NPL ratios as likely default rates in the final simulation, NPL ratios will be subject to a precautionary correction.

5.1. Simulation for NPL Ratios

We first simulate the one-step ahead (next quarter's) possible NPL ratios under baseline macroeconomic scenario. The steps of Monte Carlo simulation are as follows: (i) First the covariance matrix is decomposed into lower and upper triangular matrices by using Cholesky decomposition, such that $\Sigma = AA^T$. (ii) Then 5 independent random variables are drawn from a standard normal distribution for the vector E (iii) Independent random variables are transformed into correlated normal variables by multiplying E with A^T , lower triangular Cholesky transpose matrix. (iv) Correlated random variables are entered as the new values of residuals for VAR equations and satellite. (v) We first forecast the new values for macro variables, than by using new values of macro variables we estimate the new value of macro index. (vi) By using equation 9 we transform macro index values to NPL ratios. (vii) The above steps are repeated for 20000 times.

After completing Monte Carlo simulations for the one step ahead, we are choosing median value of the distribution as the next quarter's NPL ratio under baseline macroeconomic scenario. We go ahead with eight quarters step by step. We will use first four quarter's average as the next one year's expected NPL ratio and last four quarter's average as the second year's expected NPL ratio. The simulation results for the next eight quarters are provided in table 5.

Model estimates that system's NPL ratio which is 6.02% as of 2010Q2 will decline approximately 1.5 percentage point within 2 years under baseline macro scenario. When bearing in mind that under corrected data set, realized NPL ratios for t+1 (2010Q3) is 5.53% and for t+2 (2010Q4) is 5.23%,

performance of the model in the short run can be considered as not too bad.

Table 5. NPL Ratio Estimations Under Baseline Macroeconomic Scenario

Period	Expected NPL Ratios (%)		Expected Yearly Average (%)	
	Median	Mean	Median	Mean
t+1	5.68	5.69	5.03	5.05
t+2	5.02	5.04		
t+3	4.73	4.77		
t+4	4.67	4.71		
t+5	4.65	4.70	4.45	4.50
t+6	4.54	4.60		
t+7	4.37	4.41		
t+8	4.23	4.28		

5.2. Simulation for Loss Distribution

The first step in designing credit loss distribution simulation is to prepare a representative credit portfolio according to credit amount distribution of the system. Using available BRSA data on the subject as of 2010Q2, we construct a representative credit portfolio with 10000 credit customer. In the portfolio, 98.32% of the customers use only 29.7% of the total credit while top 0.06% use 47.86% of the total credit. We assign a fix customer number for each credit starting from 1 to 10000. In the simulation process as a principle we use binomial distribution to determine whether a customer defaulted or not for a given default probability. However, since we cannot be sure about the exact number of defaulted customers under binomial distribution, for low level probabilities we turn to uniform distribution to fix default rates and avoid underestimating. LGD is assumed 50%. Each credit amount (EAD) which is assumed as defaulted is multiplied by LGD rate. This gives us the credit loss amount for a particular defaulted customer. And the sum of losses for a particular scenario is recorded. Simulation is repeated 20000 times which means 20000 loss scenarios for each default probability. When we rank recorded loss amounts from maximum to minimum, credit loss distribution is formed and ready for analysis for a given default probability.

5.2.1. Precautionary Correction

At the first stage, we have not any other option to using estimated NPL ratios as default probabilities in the loss simulations. However we know the fact that total credit portfolio of the system is non homogeneous and customer number based default rates must be well above of the NPL ratios. We can observe this fact from the small and medium size enterprises (SME) loan portfolio of the system as BRSA publishes defaulted customer numbers for this particular portfolio lately. For instance as of June 2010 for the SME loan portfolio NPL ratio is 6.18% while the ratio of defaulted customer number to total customer number is 16.75%. Though for other retail portfolios differences may not be so big because of more fair credit amounts distributions.

Our precautionary correction based on the assumption that if the loan portfolio was to be homogeneous both mean and median of the loss

distribution would be equal or near equal to NPL ratio*LGD rate (EL rate). Differences between mean and median of the portfolio, to large extend, is the result of non homogeneity as we explained in section 2. If we increase NPL ratios to push the 'median' up to previous 'EL rate' or 'mean' level then we may move toward to the real default probabilities.

By repeating loss distribution simulations, we obtain new default probabilities for desired median levels. Desired median levels are calculated by multiplying first simulations' NPL ratios by LGD rate. Mean of the first simulation is also equal or near equal to desired median level. Precautionary correction results are given in table 6.

Table 6. Results of Precautionary Corrections for Default Rates

Year	Stage	NPL or PD	NPL*LGD	Median	Mean	Credit VaR _{99%}
1	Simulation 1	0.0503	0.02515	0.01426	0.02716	0.09567
	Simulation 2	0.0810		0.02554	0.04373	0.13849
2	Simulation 1	0.0445	0.02225	0.01240	0.02410	0.09273
	Simulation 2	0.0725		0.02223	0.03914	0.13418

As it can be seen from Table 6 the results of the correction is worth the struggle. The default probabilities increase more than 3 percentage points while the Credit VaR and economic capital requirements for 99% confidence level increase more than 4 percentage points, nearly half level of the minimum capital requirements.

5.2.2. EL and UL Estimations

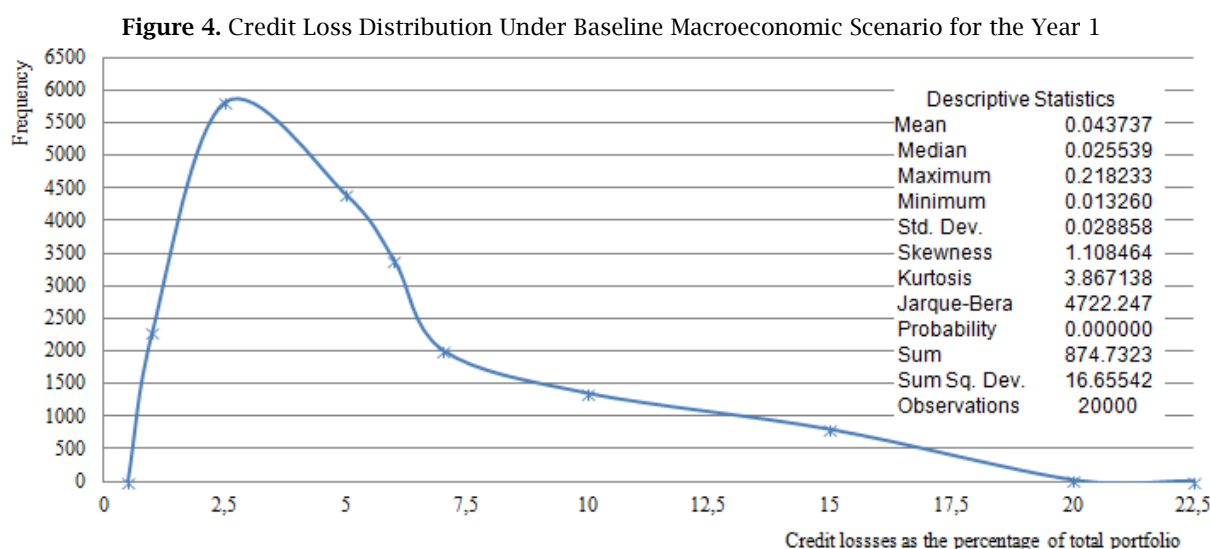
As it can be followed from Figure 4, the loss distribution we obtained shows that maximum loss 6.7 standard deviation away from the mean. Its shape and statistics comply with the literature that we touched in section 2.

We accept median value of the distribution as expected loss for reasons explained before. Credit VaR and unexpected loss calculations are made at 95% and 99% confidence levels. The results are provided in table 7.

Table 7. EL and UL Estimations Under Baseline Macroeconomic Scenario

	As the percentage of total credit portfolio	
	Year 1	Year 2
Expected Loss 50%	2.55	2.22
Unexpected Loss 95%	7.61	7.58
Unexpected Loss 99%	11.30	11.20
Credit VaR 95%	10.16	9.80
Credit VaR 99%	13.85	13.42

BRSA implements minimum Basel I capital adequacy ratio as 12% instead of 8%. We find UL of portfolio at 95% confidence level is very near to Basel I's minimum requirement for capital adequacy while UL at 99% confidence level approaches to BRSA's minimum requirements. Turkish Banking System's credit provision reserve is also well above the EL estimations.



6. STRESS TESTING

The aim of the stress testing is to analyze likely effects of 'low probability but high severity (tail) events'. They can be implemented either in the form of sensitivity analysis or scenario analysis. In the absence of the macroeconomic credit risk model sets, the only option for credit risk stress testing is very simple sensitivity analysis such as calculating effects of one percentage or one point increases in NPL ratios and default rates without relating the risk factors with the macro economic conditions. CPV approach is suitable for stochastic and deterministic scenario analysis. For instance above baseline scenario is produced in a completely stochastic process. However by manipulating innovations

(random error terms), it is possible to see likely effects of deterministic macroeconomic shocks.

With the help of covariance structure, we are able to cover not only direct effects of a particular macro variable's shock, but also indirect effects of other macro variables that are affected by the same shock. For example under the residual correlation matrix given in table 4, when we give a shock to USD variable (a shock devaluation e.g.) default rates will increase not only because of foreign exchange rate increases but also as a result of GDP contraction and interest rate raises.

In the study we test GDP shocks, combine interest rate and inflation shocks and USD/TL exchange rate shocks. To save from space, we only provide the results for GDP shocks in table 8.

Table 8. Stress Test Results for GDP Shocks

%	Base Scenario		- 1%		- 5%		- 10%	
	Year 1	Year 2	Year 1	Year 2	Year 1	Year 2	Year 1	Year 2
NPL	5.03	4.45	5.78	5.68	6.18	6.28	6.73	7.24
PD	8.10	7.25	9.30	9.25	9.70	9.80	10.20	10.40
EL %50	2.55	2.22	2.89	2.85	3.08	3.12	3.35	3.62
UL %95	7.61	7.58	7.55	7.56	7.51	7.48	7.43	7.24
UL%99	11.30	11.20	11.30	11.24	11.12	11.19	11.18	10.94
Credit VaR %95	10.16	9.80	10.44	10.41	10.59	10.60	10.78	10.86
Credit VaR % 99	13.85	13.42	14.19	14.09	14.20	14.31	14.53	14.56

We use three scenarios for GDP contraction. GDP contracts four successive quarters 1%, 5% and %10 on a yearly basis. Shocks represent a weak, a mild, and a severe recession. Turkey's economy has experienced a heavy recession by contracting 6.97%, 14.57%, 7.65% and 2.66% four consecutive quarters from 2008Q4 to 2009Q3. The average was 7.76% for a period of one year. Hence, our scenarios are realistic in nature and the test results are comparable with the past performance of the economy.

NPL ratio average for the recession period was 5.06% and for the post-recession period (from 2009Q4-2010Q3) it was 6.02%. One year average of NPL ratios for pre-recession period (from 2007Q4-2008Q3) was 3.81%. In other words NPL ratios increased 1.25 percentage point during the recession period, and even the economy started growing NPL ratios increased 0.96 percentage point further in the following year.

Actually experienced near-past performance of the economy and the banking system justify the stress test results. Though it is possible to think it is normal because model itself, is based on historical data, but it is also an evidence of model consistency.

When we compare the stress scenarios' results with the baseline scenario, increases in NPL ratios for the first year are 0.75, 1.15, 1.70 percentage points and for the second year are 1.20, 1.60 and 2.10 percentage points accordingly. They are very well compatible with the past experiences.

In the analysis we use unconditional default rates, if we switch to conditional default rates for the second years (on the condition that customers did not default in the first year), probability of default and credit losses might increase further. But it is interesting to see much of the increases in the total risk (credit VaR) goes to EL rather than UL.

And finally, it might be useful to underline the fact that relations between macro shock levels and

credit risk indicators are not linear, even though satellite model is estimated with linear regression. It shows the impact of logistic transformation.

7. SUMMARY AND CONCLUDING REMARKS

In this study by adapting Wilson's CPV approach, we developed a macroeconomic credit risk stress testing model set for the Turkish banking system. Developed models confirm the strong statistical relationship between systematic component of credit risk and macroeconomic variables in Turkey. Stress test results also are compatible with the past experiences.

However one important aim of this study is to underline and limit some ignored problems using accounting based NPL ratios as default rates in macroeconomic credit risk modeling, a common practice for many countries where historical default rates are not available.

Since customer number based historical default rates are not available for the whole Turkish banking system's credit portfolio, we too used NPL ratios as dependent variable instead of default rates, at the first stage. However we tried to overcome some of the problems such as underestimating portfolio losses as a result of totally non-homogeneous total credit portfolios and transferring non-performing loans from banks' balance sheets to asset management companies.

On the other hand, we gave particular importance working with the lagged values of independent variables since it is possible to encounter entirely opposite results with regard to the effects of macro variables on defaults. We think in a dynamic model, the aim of which is to estimate future paths of variables in a continuous manner, even contradictory impacts on the dependent variable at the different time lags has to be taken into consideration as long as a meaningful explanation does exist.

To avoid underestimating credit losses we corrected data set for transferred non-performing loans. As of 2010Q2 total value of re-added non-performing loans to the nominator of the ratio has reached 16% of the total non-performing portfolio.

And before using NPL ratios as default probabilities in the final credit loss simulations we made a huge precautionary correction based on the assumption that if the loan portfolio was to be homogeneous both mean and median of the loss distribution would be equal or near equal to NPL ratio*LGD rate (EL rate). Hence, if we increase NPL ratios to push the 'median' up to previous 'EL rate' or 'mean' level by repeating simulations, then we may move toward to the real default probabilities.

The result of the precautionary correction is worth the struggle. The default probabilities increase more than three percentage points while the Credit VaR and economic capital requirements for 99% confidence level increase more than four percentage points, nearly half level of the minimum capital requirements.

There are still problems that we could not address such as the inclusion of off-balance sheet credits to the analysis, because of data limitations.

Our study show that using accounting based NPL ratios as default rates, without addressing obvious problems, may not be so healthy, particularly in practices such as macroeconomic

credit risk stress testing that are carried out to test the health of the banking systems of the countries.

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