A Macro-econometric Model for Stress Testing Credit Portfolio

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This paper attempts to develop a macro-econometric credit risk model for Turkish banking system and use it in stress testing. For this, we apply a revised version of Credit Portfolio View model to Turkish credit data which includes total banking systems' corporate loan portfolio. In the constructed empirical model, first changes in the non-performing loan ratios of eight different sectors were explained by some macroeconomic variables. Then the evolutions of the macro variables were estimated by using ARIMA type models. The residuals obtained in both of the steps were used to construct the covariance matrix for the system of equations. By using the system of equations and their covariance structure, a Monte Carlo simulation was done to simulate one-step-ahead unconditional portfolio losses. Stress-tests are performed by using historical shocks for macro variables and conditional portfolio losses are calculated. The expected and unexpected losses are calculated from the loss distributions and the risk bearing capacity of Turkish banking system is analyzed.

Keywords: Credit risk, credit portfolio view, stress-test, Monte Carlo simulation, Turkish banking

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I. Introduction

Credit risk is the most important type of risk for banks. Although the type of products banks offer change continuously, they generally include a credit risk component. Tools and techniques used for measuring and managing credit risk have also been improved by time. Now, managing credit risk means an active portfolio management of credit-related instruments, by also using advanced quantitative models.

Because of its importance, credit risk is the first type of risk that is subject to strict regulatory oversight. Backed by extensive policy debate, the approach for regulation and supervision of credit risk has also evolved. Especially, after the issuance of Basel-II on 2004 (BCBS 2004) the debate on credit risk has accelerated. The second pillar of Basel-II requires performing stress tests for different risk types. Therefore, after the issuance of Basel-II, one of the main areas that regulators focus is stress testing. Additionally, the initiation of the Financial Sector Assessment Programs (FSAP) by the IMF and World Bank to identify the vulnerabilities in the financial systems of their member countries accelerates the literature on macro-prudential assessment of banking systems.

Although statistical modeling approaches were first appeared in market risk modeling, there was a rapid growth in the literature related to credit risk modeling in the past decade. For credit risk, there are lots of modeling approaches in academic literature, but due to the lack of some critical data and other practical problems only a few of them are used by practitioners. In credit portfolio modeling, there are three commonly used approaches. The first one is based on the Merton's (1974) model which uses the option pricing approach to estimate the firm's probability of default (PD). Two widely known commercial models, KMV's *Portfolio Manager (PM)* and JP Morgan's *Credit Metrics^{TM} (CM^{TM})*, use Merton's approach with different techniques and variables. The second type of credit portfolio models is Credit Suisse Financial Products' *CreditRisk^{+} (CR^{+})*. This model uses actuarial approaches to estimate the portfolio loss distributions by using historical default rates and their volatilities. And the final type of model is the *Credit Portfolio View (CPV)* model developed by Wilson (1997a and 1997b) of KPMG. In CPV, the default and other rating migration probabilities are explicitly linked to some macroeconomic variables and distribution of portfolio losses are calculated by using Monte Carlo simulations. These three modeling approaches are based on different assumptions and use different techniques requiring different sets of variables.

In this paper, a revised version of CPV is applied to Turkish credit data which includes total banking systems' corporate loan portfolio. The structure of the paper is as follows: Section II begins with the general framework of credit risk models and then explains the strong linkage between credit risk and macroeconomic environment. The empirical literature on macro-econometric modeling of credit risk is also given in this section. The details of the CPV model are given in section III. Section IV gives the empirical model that is developed for Turkish banking system. In this section, first the characteristics of data are introduced. Then each step of the modeling is explained in a detailed manner. Sections V and VI are devoted to the simulation and stress testing of portfolio losses. Conclusions are given in section VII.

II. Credit Risk Modeling

There are different modeling approaches used for estimating the credit portfolio losses. On the surface, these credit risk portfolio models seem to be quiet different. However, Koyluoglu and Hickman (1998) show that these models belong to a single general framework. They conclude that the differences in model results are to a lesser extent due to the model methodology or distributional assumptions, but rather to different ways of approximating the default correlations that are empirically hardly available.

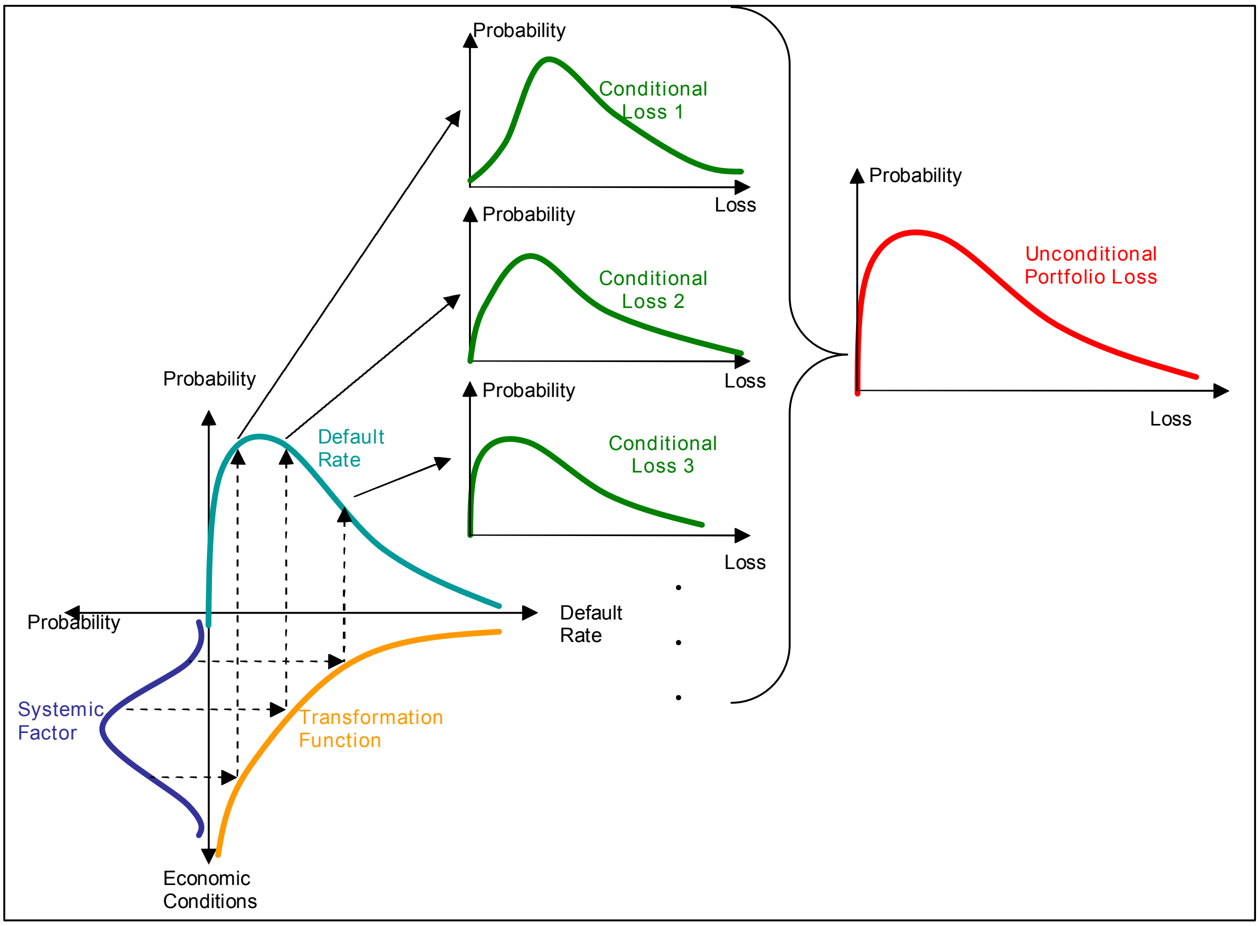
Credit Risk Modeling – General Framework

Koyluoglu & Hickman (1998) show that the three credit portfolio modeling approaches mentioned above have a common framework and models the portfolio losses in three steps. They show that, although all the models do not explicitly use these three steps, all use them in an explicit or implicit manner and show how to define the implicit steps in each model. These steps are defined as follows:

- *Joint-default behavior* – In all models, the default process can be explained by two components. The first component is the 'systematic component'. This represents the effects of some systematic factors on firm default. The systematic factors can be thought as variables representing general economic conditions or other drivers of defaults. The second component of default process is the 'idiosynatric component', which represents firm-specific issues. In models, the idiosynatric components are assumed to be independent of each other, as well as the systematic components. In the fist step, a conditional default rate is generated for each borrower, for each possible outcome of systematic factors. When we fix the value of systematic component, the remaining uncertainty will be caused by only the idiosynatric component. And since idiosynatric components are independent across firms, the conditional firm default behavior becomes independent. This means that the correlation structure of firm defaults can be attributed to the dependence of obligors to the same systematic factors.
- *Conditional distribution of portfolio default rate* – In the second step, conditional loss distributions are generated for each possible outcome of systematic factors. Since all the joint default behavior has been captured in the first step, the conditional default processes are assumed to be independent in the second step. Therefore, conditional loss distributions are generated by using independent defaults, an assumed loss process given default and exposure amounts.
- *Convolution / Aggregation* – In the final step, conditional loss distributions are aggregated by using respective probability distribution for systematic factors. This gives us the unconditional loss distribution of the portfolio.

These steps are summarized in figure 1. When we obtain the portfolio loss distribution we can easily calculate all the statistics, i.e. mean (expected loss – EL), standard deviation, extreme losses for given percentiles (unexpected loss – UL), expected extreme losses beyond given percentiles (expected shortfall), etc.

Figure 1: General Framework for Credit Risk Models



Source: Koyluoglu & Hickman (1998).

Macro-econometric Modeling of Credit Risk

Explicitly linking credit risk to macroeconomic factors has both theoretical reasoning and empirical evidence. The basic intuition is that when the economy is in recession, more firms incur losses and go into default or bankruptcy. Or the asset values will decline such that the collaterals will worth less. There are strong empirical findings showing the effects of macro economic factors on different elements of credit risk (i.e. probability of defaults – PD, loss given defaults – LGD). Interested readers should consult to Allen and Saunders (2003) for a comprehensive survey.

The relationship between credit risk and macroeconomic factors can be in any type. This relation may include the effects on PD only, or both on PD and LGD. And the functional form can be chosen in a flexible manner to capture the best fit to the empirical data.

Due to its intuitive advantages and analytical tractability, macro-econometric modeling of credit risk become a powerful tool for macro-prudential assessments and commonly used by many practioners, supervisory authorities as well as IMF and WB (see Blaschke et al., 2001).

Empirical Literature

There are different studies which used different versions macro-econometric credit risk models on countries' whole banking systems. Most of these studies explain the approaches and results of works done under the FSAP programmes. The following studies include both the models with endogenous or exogenous macro variables.

For example, in the FSAP of Germany, IMF and Deutsche Bundesbank used a macro-econometric model for modeling the specific provisions charged for loans (see Deutsche Bundesbank, 2003). They used GDP growth, credit expansion and real interest rates to explain the changes in provisions, and used this model to simulate and stress test the overall banking system's credit risk.

As a part of the FSAP programme, IMF, FSA and Bank of England used a macro model (see Hoggart and Whitley, 2003 and Hoggarth, Logan and Zicchino, 2003) to explain the changes in credit provisions with 5 explanatory variables: GDP growth for UK and the whole world, real interest rates, money supply and the Herfindahl index to measure the concentration in loan portfolios. The model is used to stress test the credit losses and the paper concluded that current level of UK banks' profits would seem to be sufficient to cover a decline in credit quality and increase in loss experience associated with a year of recession conditions.

Kalirai and Scheicher (2002) models the loan loss provisioning ratio in Austrian banking system by using 9 macro variables chosen from 31 candidates by using data from 1990 to 2001. The model is used to simulate and stress test the credit losses in Australian banking system. When compared with the current level banking capital the results seems to be very moderate.

Boss (2002) models the default rates observed in banking loans in Austria from 1965 to 2001. The CPV model was used and the default rates are explained by 8 different macro variables chosen from 31 candidates (the same 31 variables used in Kalirai and Scheicher, 2002). The model is used to simulate and stress test the credit losses in Australian banking system and concluded that Austrian banks' risk-bearing capacity is more than adequate.

Kearns (2004) models the loan loss provisioning ratio in Irish banking system by using GDP, unemployment rate, banks' earnings, growth in loan stock, share of loans in total assets and ratio of capital to total assets. The model is used to stress test the credit losses in Australian banking system for a 3-year horizon. The results suggest no threats to the banks.

Virolainen (2004) applied CPV model on industry-specific corporate sector bankruptcies over the time period from 1986 to 2003 and estimate a macroeconomic credit risk model for the Finnish corporate sector. The results suggest a significant relationship between corporate sector default rates and key macroeconomic factors including GDP, interest rates and corporate indebtedness. The estimated model is employed to analyse corporate credit risks conditional on current macroeconomic conditions. Furthermore, the paper presents some examples of applying the model to macro stress testing, i.e. analysing the effects of various adverse macroeconomic events on the banks' credit risks stemming from the corporate sector. The results of the stress tests suggest that Finnish corporate sector credit risks are fairly limited in the current macroeconomic environment.

In its original form CPV does not require any data on borrower ratings or market data on borrowers' equity. However there are some attempts to combine the CPV methodology with additional market data as well as rating data. Examples of such attempts include Pesaran (2003), Lily and Hong (2004), Carling et al. (2002) and Peura and Jokivuolle (2003).

III. CPV Model

The basic idea of the CPV model is to link default and migration probabilities to macro variables. The CPV model can be applied for a 'mark-to-market' or a 'default-mode' framework. In the first case, the losses stemming from credit portfolio includes mar-to-market valuation losses, while in the second case, only losses caused by defaults are considered. Here, we summarize the steps of CPV model for a default-mode framework. The full details of the model, including mark-to-market framework, is explained in Wilson (1997a, 1997b and 1998).

The default-mode CPV model has four steps. In the first step, average default rates are linked to some macro indices. These indices can be seen as functions of different macro variables. In the second step, the evolutions of macro variables are described by using time-series models. The third step is the construction of the correlation structure of model. In the final step, new values for macro variables and average default rates are simulated and portfolio loss distribution is generated.

In the first step, the average default rate for each industry is linked to macro index by using a logistic transformation:

$$p_{j,t} = \frac{1}{1 + e^{y_{j,t}}} \tag{1}$$

where $p_{j,t}$ is the default rate in industry j at time t, and $y_{j,t}$ is the industry-specific macroeconomic index. The logistic transformation ensures that the value of default rates are in the range [0,1]. From equation (1), the value of macro index given default rate is calculated as:

$$y_{j,t} = \ln\left(\frac{1 - p_{j,t}}{p_{j,t}}\right) \tag{2}$$

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, i.e.:

$$y_{j,t} = \beta_{j,0} + \beta_{j,1} x_{1,t} + \beta_{j,2} x_{2,t} + \ldots\ldots.. + \beta_{j,n} x_{n,t} + \upsilon_{j,t} \tag{3}$$

where β_j is a set of regression coefficients to be estimated for the j^{th} industry, $x_{i,t}$ (i = 1, 2,…, n) is the set of explanatory macroeconomic factors (eg GDP, interest rates etc.), and $\upsilon_{j,t}$ 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. In equation (3), the systematic effect is captured by macroeconomic variables $x_{i,t}$, and $\upsilon_{j,t}$ defines a sector-specific surprise. In empirical model, equation (3) should be estimated for each sector in order to allow the explanatory macro variables to differ between sectors.

In the second step, the evolutions of individual macro variables are modeled by using time-series models. For this step, Wilson (1997a, 1997b) originally (and also Boss, 2002 and Virolainen, 2004) used a simple AR(2) process but added that different ARMA structures[3] may be used.

For illustration purposes, assume that for all macro variables, second-order autoregressive models are used:

$$x_{i,t} = \gamma_{i,0} + \gamma_{i,1} x_{i,t-1} + \gamma_{i,2} x_{i,t-2} + \varepsilon_{i,t} \tag{4}$$

where k_i is a set of regression coefficients to be estimated for the i^{th} macroeconomic factor, and $\varepsilon_{i,t}$ is a random error assumed to be independent and identically normally distributed.

In the third step, correlation structure of the model is constructed. The empirical models for each sector estimated by using equation (3), together with empirical models for each macro variable estimated by using equation (4) define a system of equations. The system has a $(J + I) \times 1$ vector of error terms, or innovations, E, and a $(J + I) \times (J + I)$ variance-covariance matrix of errors, Σ, defined by:

$$E = \begin{pmatrix} \upsilon \\ \varepsilon \end{pmatrix} \sim N(0, \Sigma) \quad , \quad \Sigma = \begin{bmatrix} \Sigma_{\upsilon} & \Sigma_{\upsilon,\varepsilon} \\ \Sigma_{\varepsilon,\upsilon} & \Sigma_{\varepsilon} \end{bmatrix} \tag{5}$$

The final step is the simulation of portfolio losses. In this step, first, random innovations are generated by using the covariance structure estimated in the previous step. Then future values of macro variables and default rates are calculated. And finally, by using LGD values and exposure amounts, portfolio loss distribution is calculated. Moreover, it is also possible to analyze various macroeconomic stress scenarios with the model.

IV. Empirical Model

Since there is no available data for sectoral default rates for Turkey, in the empirical model, we attempt to explain the developments in NPL ratios with the developments in some macro variables. The historical data used in the empirical model has the interesting property that it also includes the crisis period. Turkey has experienced a severe banking and foreign exchange crisis period in 2001 in which 19 banks were taken over. After the crisis, tight fiscal and monetary policies were implemented and the economy went through a transition period. In this period, the fundamental macro indicators have started to improve, such as declining interest rates and inflation rates as well as GNP growth. The improvements in the macro

[3] Indeed, for this step any type of model can be used.

economy also lead to improvements in Turkish banking system. The system, which experienced huge losses from government securities as well as non-performing loans (NPL), started to recover itself beginning with year 2002. In the transition period, there are also some structural changes in the banking system. For instance, the share of loans in total assets increased from its the traditionally low levels of 20% to approximately 30%.And the share of consumer loans in total loans increased from 11% in 2001, to approximately 30% in 2005. Additionally, a recapitalization program was conducted by BRSA in 2002, in which banks were subject to a three-staged audit process. The main aim of the program was assessment of the capitalization needs of banks and at the end of the program there were significant changes in the NPL amounts for many banks.

Data

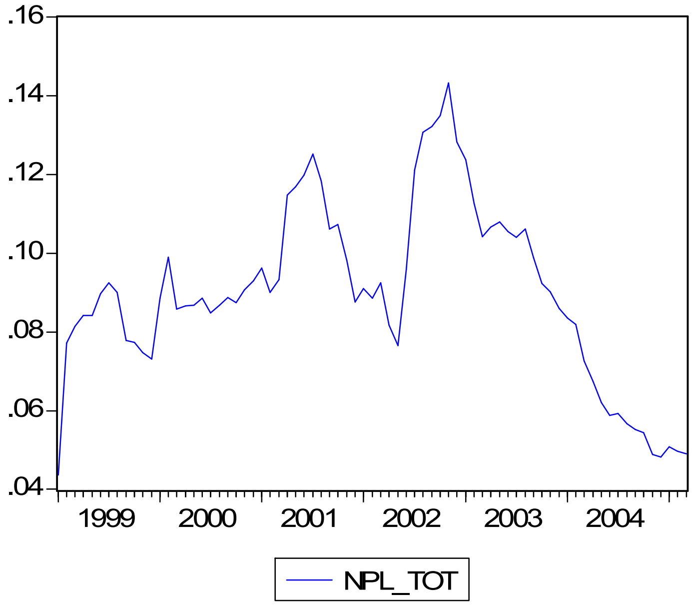
In this study, NPL ratios[4] of different sectors are used as dependent variables. The data on total performing and non-performing loans are available for 31 different sectors (including sub-sectors) from January 1999 to March 2005 on a monthly basis in the Central Bank's web site[5]. The data set also includes the crisis data. These data are grouped into 8 broad sectors[6] and NPL ratios are calculated for each sector. Data for Dec 1999 is dummied out for 3 sectors (financial, agriculture, other) as it seems to be a huge outlier. The descriptive statistics and the graph of total NPL ratio is given in table 1 and graph 1.

Table 1: Descriptive Statistics for NPL Ratios of Different Sectors

	CON	ENG	FIN	MAN	OTH	SER	TRD	AGR
Mean	0.082910	0.019283	0.058470	0.109254	0.063216	0.079361	0.095138	0.084510
Median	0.080247	0.010112	0.041320	0.107650	0.046138	0.084154	0.068595	0.074009
Maximum	0.148306	0.054058	0.192376	0.165556	0.216133	0.138399	0.285739	0.438216
Minimum	0.003958	0.005227	0.013520	0.050384	0.002785	0.032365	0.034903	0.032315
Std. Dev.	0.034944	0.014356	0.039528	0.026624	0.048910	0.029307	0.064039	0.054543
Skewness	0.281035	1.033797	1.289838	-0.07036	1.643783	0.153861	1.274543	4.083011
Kurtosis	2.103106	2.862600	3.837228	2.831436	5.095140	1.708182	3.423805	24.75473
Jarque-Bera	3.594430	13.77600	23.59946	0.154701	48.75930	5.657854	21.42347	1732.346
Probability	0.165760	0.001020	0.000008	0.925566	0.000000	0.059076	0.000022	0.000000
Sum	6.384048	1.484770	4.502188	8.412554	4.867655	6.110786	7.325627	6.507295
Sum Sq.Dev.	0.092802	0.015664	0.118749	0.053870	0.181804	0.065277	0.311680	0.226096
Observations	77	77	77	77	77	77	77	77

[4] Non-performing Loans / (Performing Loans + Non-performing Loans)
[5] www.tcmb.gov.tr
[6] Sectors: Agriculture (AGR), Construction (CON), Energy (ENG), Finance (FIN), Manufacturing (MAN), Service (SER), Trade (TRD), Other (OTH).

Graph 1: Total NPL Ratio



As seen from the graph, there are two significant jumps in the NPL ratios. The first one in 2001 is due to the economic crisis; however the second one in 2002 is due to the recapitalization program.

In the empirical model, 11 macro variables are tested for their explanatory power. These are gross national product (GNP), Istanbul Stock Exchange-100 Index (ISE), Euro/New Turkish Lira rate (EUR) and USD/ New Turkish Lira rate (USD), interest rate (IR), unemployment rate (UR), current account balance (CUR), consumer price index (CPI), total domestic loans of the banking system (CRD), industrial production index (IPI) and money supply (M3Y). These data are obtained from the web sites of Banking Regulation and Supervision Agency, Central Bank, State Planning Institution and Turkish Statistical Institute[7]. All of the macro data, except GNP and UNM, is available on a monthly basis or more frequent. The GNP and UNM are linearly interpolated to construct a monthly data series and growth rates are re-calculated by using this data set. The descriptive statistics for macro variables are given in table 2.

Table 2: Descriptive Statistics for Macro Variables

	Mean	Median	Maximum	Minimum	Std. Dev.	Skew.	Kurt.	Jarque-Bera	Obs.
CPI	4.0	3.8	24.7	-0.9	2.7	2.2	17.4	2186.0	232
CRD	13411370.0	949065.0	94900868.0	5056.0	21250163.0	1.9	6.1	229.7	233
CUR	-350.5	-230.5	1596.0	-2939.0	820.0	-0.9	4.1	31.7	168
EUR	1216235.0	1359946.0	1881555.0	376465.7	535415.2	-0.3	1.5	9.3	78
GNP	25516.7	25168.7	41883.0	13407.0	5999.8	0.3	2.5	4.9	217
IPI	105.8	104.0	133.0	81.0	12.4	0.4	2.6	4.0	102
IR	53.7	52.8	344.1	19.3	27.7	5.1	52.7	25050.7	234
ISE100	4833.1	470.0	28396.0	1.0	7061.0	1.5	4.2	95.2	234
M3Y	72743721.0	51129867.0	203000000.0	174078.0	65141536.0	0.5	1.8	12.1	118
UNM	8.1	7.8	12.4	5.6	1.5	0.9	3.3	25.7	175
USD	410928.5	49770.0	1708213.0	581.1	578726.2	1.1	2.6	51.2	234

[7] www.bddk.org.tr, www.tcmb.gov.tr, www.dpt.gov.tr, www.turkstat.gov.tr .

Modeling NPL Ratios

In order to model the NPL ratios, first the NPL ratios are transformed by using logit transformation (i.e. equation 2). We use a slightly different formula from equation 2 and include a minus sign for the index:

$$NPL_{j,t} = \frac{1}{1+e^{-y_{j,t}}} \quad \Rightarrow \quad y_{j,t} = \ln\left(\frac{NPL_{j,t}}{1-NPL_{j,t}}\right) \tag{6}$$

While most of the indices (y) have unit roots (see table 3 below), we use annual logarithmic growth rates for sectoral indices:

$$y^*_{j,t} = \ln\left(\frac{y_{j,t}}{y_{j,t-12}}\right) \tag{7}$$

Table 3: Augmented Dickey-Fuller Test Statistics for Sectoral Indices (y)

Sector	t-Statistic	Probability
AGR	0.516538	0.8246
CON	-0.42594	0.5259
ENG	0.317318	0.7745
FIN	0.336708	0.7797
MAN	0.813251	0.8854
OTH	-0.50652	0.4934
SER	-0.31688	0.5678
TRD	-0.50761	0.4930

The transformation removes unit root for 6 sectors. For the remaining 2 sectors, we also perform a Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test to check whether the series is stationary or not. The test results suggest stationarity. The test statistics for ADF and KPSS tests are presented in table 4.

Table 4: Augmented Dickey-Fuller and KPSS Test Statistics for Transformed Indices (y^*)

			KPSS Test			
Sector	t-Statistic	Probability	LM Stat	% 1 Level	% 5 Level	% 10 Level
AGR	-2.4897	0.0136				
CON	-2.0059	0.0438				
ENG	-1.9941	0.0450				
FIN	-1.7018	0.0839				
MAN	-1.3716	0.1562	0.553	0.739	0.463	0.347
OTH	-2.3856	0.0178				
SER	-2.3251	0.0206				
TRD	-1.3652	0.1580	0.377	0.739	0.463	0.347

In order to explain the annual changes in sectoral indices (y^*), we estimate the empirical model by using its first lag and annual growth in macro variables:

$$y^*_{j,t} = \beta_{j,0} + \beta_{j,1} y^*_{j,t-1} + \beta_{j,2} x^*_{1,t} + \beta_{j,3} x^*_{2,t} + \dots\dots\dots + \beta_{j,n+1} x^*_{n,t} + \upsilon_{j,t} \tag{8}$$

where $X^{*}_{k,t}$ is the set of transformed macro variables for each sector:

$$x^{*}_{i,t} = \ln\left(\frac{x_{i,t}}{x_{i,t-12}}\right) \tag{9}$$

We also test for the significance of a dummy variable for months in the third quarter of 2002, which represents the effects of recapitalization program. However, since the transformed indices represent the annual changes in NPL ratios, the dummy variable is not significant for most of the sectors. Therefore we select not to use a dummy variable.

We search for the best regression and stop when we have an equation in which all the variables are significant and have the expected sign, and residuals do not contain autocorrelation (tested by using Breusch-Godfrey Serial Correlation LM Test). Also we use Newey-West heteroskedasticity consistent estimation procedures. Additionally, we do not use USD and EUR, GNP and IPI, CPI and M3Y at the same equation in order to eliminate near collinearities. The selected regression equations are given table 5.

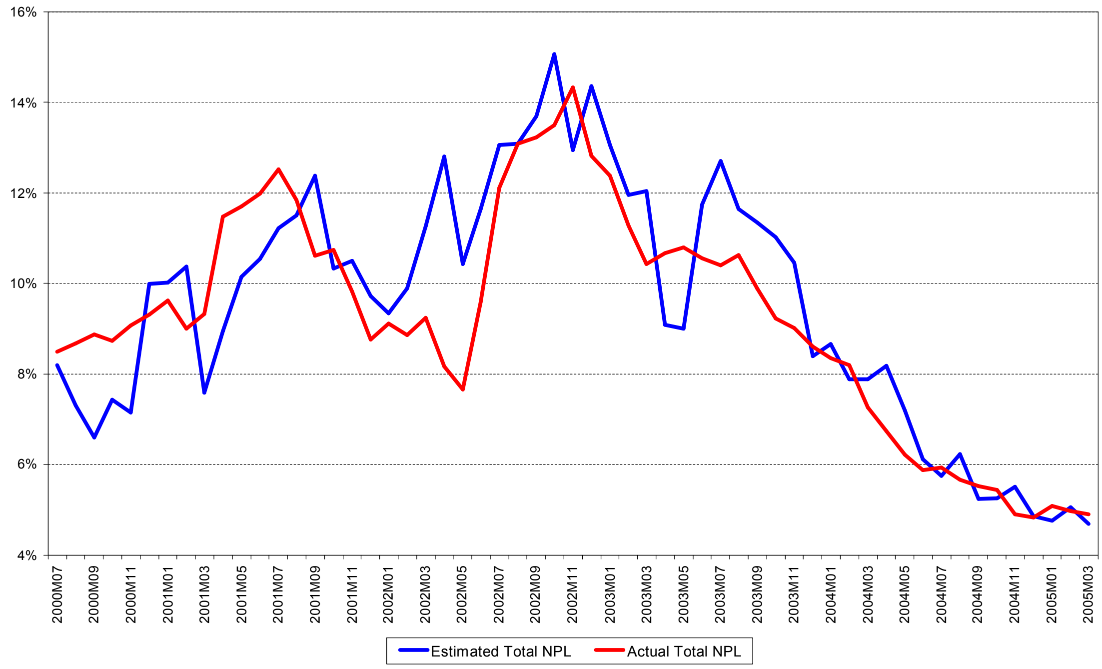
Table 5: Regression Results for Sectoral Indices

		AGR	CON	ENG	FIN	MAN	SER	TRD	OTH
Constant	Coefficient	0.0083	-0.0338	0.0281	0.0599	-0.1117	0.0356	-0.2134	0.0257
	Std. Error	0.0072	0.0332	0.0114	0.0275	0.0274	0.0199	0.0754	0.0455
	t-Statistic	1.14	-1.02	2.46	2.18	-4.07	1.79	-2.83	0.56
	Prob.	25.93%	31.42%	1.71%	3.38%	0.02%	7.91%	0.66%	57.48%
First Lag of Dep. Variable	Coefficient	0.8541	0.6059	0.4481	0.8935	0.7569	0.6762	0.7058	0.7382
	Std. Error	0.0425	0.1093	0.0838	0.0704	0.0598	0.1067	0.0844	0.0493
	t-Statistic	20.09	5.54	5.35	12.69	12.65	6.33	8.36	14.96
	Prob.	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
CRD	Coefficient		0.2092			0.3086		0.8828	
	Std. Error		0.0990			0.0661		0.2675	
	t-Statistic		2.11			4.67		3.30	
	Prob.		3.93%			0.00%		0.18%	
CUR	Coefficient	-0.0001				-0.0001			-0.0001
	Std. Error	0.0000				0.0000			0.0000
	t-Statistic	-2.95				-4.26			-1.87
	Prob.	0.48%				0.01%			6.67%
GNP	Coefficient	-0.3840							
	Std. Error	0.1771							
	t-Statistic	-2.17							
	Prob.	3.49%							
EUR	Coefficient				0.1942			-0.4210	-0.3180
	Std. Error				0.1108			0.1258	0.1229
	t-Statistic				1.75			-3.35	-2.59
	Prob.				8.57%			0.15%	1.26%
IR	Coefficient			0.0444					
	Std. Error			0.0174					
	t-Statistic			2.55					
	Prob.			1.36%					
CPI	Coefficient				-0.3593				
	Std. Error				0.1434				
	t-Statistic				-2.51				
	Prob.				1.54%				
UNM	Coefficient		0.5247	0.4145		0.2696	0.2246	0.7784	0.5641
	Std. Error		0.1651	0.0775		0.0666	0.1206	0.2343	0.1729
	t-Statistic		3.18	5.35		4.05	1.86	3.32	3.26
	Prob.		0.25%	0.00%		0.02%	6.81%	0.16%	0.20%
USD	Coefficient		-0.2543				-0.1633		
	Std. Error		0.0970				0.0730		
	t-Statistic		-2.62				-2.24		
	Prob.		1.15%				2.96%		
	R-squared	90.7%	85.6%	84.2%	81.3%	87.4%	78.5%	90.8%	89.9%
	Adjusted R-squared	90.1%	84.5%	83.3%	80.2%	86.4%	77.3%	90.1%	89.1%
	S.E. of regression	0.057	0.081	0.067	0.123	0.060	0.092	0.143	0.137

The selected equations include eight different macro variables out of eleven. And each equation includes different explanatory variables. In every equation, the first lags of dependent variables have very high t-statistics. Among macro variables, unemployment rate is the most common variable. Also the foreign exchange rates (USD and EUR) appear in 5 different equations. An interesting result is that GNP, CPI and IR appear in only one equation.

The estimation results suggest very high R^2 values. This can also be verified by visual inspection of fit from graph of actual-vs-estimated NPL ratios (see graph 2).

Graph 2: Actual vs. Estimated NPL Ratios (for all sectors)



Modeling Macro Variables

After modeling the NPL ratios for each sector, the evolution of macro variables are modeled by using ARIMA structures. The steps are summarized below:

- First the time series of 8 transformed macro variables (x^*) are tested for unit root by using Augmented Dickey-Fuller Test.
- If the variable has a unit root, a new data set was created by differencing. Otherwise, original data series was used.
- The evolution of the selected data series is estimated by ARMA-type models including the seasonality adjustments.
- In order to determine the best ARMA structure, first correlograms and Q-statistics were analyzed.
- Then different ARMA structures are tested and the best structure was determined by using following criteria:
    - Significance of coefficients
    - Schwarz Bayesian Information Criteria
    - Absence of autocorrelation in residuals (Tested by Q-stats)
    - Parsimony

- Invertability (stationarity) of autoregressive roots
- Visual inspection of fit

The general specification for ARMA models, including seasonal autoregressive terms is:

$$\Psi(L)\Phi(L)x_t^* = \mu + \Theta(L)\varepsilon_t \tag{10}$$

where:

- L is the lag operator such that $L^n x_t^* = x_{t-n}^*$
- $\Psi(L) = (1 - L^s)$ is the seasonal autoregressive polynomial with seasonal term s
- $\Phi(L) = 1 - \varphi_1 L - \varphi_2 L^2 - ..... - \varphi_p L^p$ is the auto regressive polynomial
- $\Theta(L) = 1 + \theta_1 L + \theta_2 L^2 + ... + \theta_q L^q$ is the moving average polynomial
- ε_t is the error term.

The best ARMA structures are summarized in table 6.

Table 6: ARMA Structures for Macro Variables

Variable	Transformation	ARMA Terms†	Adj. R^2
CPI	Differencing	AR(1), SAR(12)	63,05%
CRD	Differencing	AR(12) , MA(3)	18,08%
EUR	Differencing	AR(1), SAR(12)	37,39%
USD	Differencing	AR(1), SAR(12)	35,65%
IR	No	AR(1), AR(2), SAR(12)	72,60%
UNM	No	AR(1), AR(2), SAR(12), MA(3)	98,32%
GNP	No	AR(1), AR(2), SAR(12), MA(3)	98,45%
CUR	No	AR(1), AR(2), SAR(12)	59,92%

† *AR: Autoregressive term*
MA: Moving average term
SAR: Seasonal autoregressive term

While the transformed macro variables (x^*) indicates 12-month growth rates, the ARMA structures generally includes AR(12) or SAR(12) terms. Also, AR(1) term appears in all except one equation.

Covariance Structure

After estimating the NPL ratio models for each sector and estimating the ARIMA structures for each macro variable, the correlation structure between these estimations are set up by using the covariances between residuals of these estimations. This correlation matrix is given in table 7.

Table 7: Correlation Structure of the Entire Model

	AGR	CON	ENG	FIN	MAN	OTH	SER	TRD	CPI	CRD	CUR	EUR	GNP	IR	UNM	USD
AGR	1.0000	0.1931	-0.2060	0.2382	0.1790	0.0258	0.1127	-0.0016	0.0439	0.1209	0.0233	-0.0587	0.2000	0.2375	-0.3676	-0.0394
CON	0.1931	1.0000	-0.0810	0.5713	0.4763	0.1891	0.0754	-0.0591	-0.0984	0.1392	-0.1714	-0.0655	0.1138	0.0811	-0.1921	-0.0467
ENG	-0.2060	-0.0810	1.0000	0.1096	0.1463	-0.0537	0.4708	0.1339	0.3022	-0.0433	0.0044	0.2089	-0.3420	-0.1315	-0.2796	0.2245
FIN	0.2382	0.5713	0.1096	1.0000	0.4014	0.2467	0.1078	0.0286	-0.2408	0.2199	-0.1478	0.0121	0.0467	0.1468	-0.2212	0.1136
MAN	0.1790	0.4763	0.1463	0.4014	1.0000	0.4301	0.3183	0.0526	-0.3725	0.1277	0.0462	0.0857	-0.0021	0.0793	-0.2214	0.1421
OTH	0.0258	0.1891	-0.0537	0.2467	0.4301	1.0000	0.4886	0.3595	-0.1736	0.1541	0.1219	0.2351	0.1396	0.1579	0.1538	0.1938
SER	0.1127	0.0754	0.4708	0.1078	0.3183	0.4886	1.0000	0.2787	0.0522	0.1126	-0.2032	0.2481	-0.0102	0.0606	-0.0331	0.2524
TRD	-0.0016	-0.0591	0.1339	0.0286	0.0526	0.3595	0.2787	1.0000	0.0165	0.0578	0.0292	0.1566	-0.0007	-0.1386	-0.0208	0.1652
CPI	0.0439	-0.0984	0.3022	-0.2408	-0.3725	-0.1736	0.0522	0.0165	1.0000	-0.0654	0.2712	0.1524	-0.2055	-0.1690	-0.3259	0.0685
CRD	0.1209	0.1392	-0.0433	0.2199	0.1277	0.1541	0.1126	0.0578	-0.0654	1.0000	-0.2338	0.4684	0.1759	0.0282	-0.0410	0.4905
CUR	0.0233	-0.1714	0.0044	-0.1478	0.0462	0.1219	-0.2032	0.0292	0.2712	-0.2338	1.0000	0.0902	-0.3959	0.0266	0.0167	0.1033
EUR	-0.0587	-0.0655	0.2089	0.0121	0.0857	0.2351	0.2481	0.1566	0.1524	0.4684	0.0902	1.0000	-0.1071	0.1896	0.0204	0.8886
GNP	0.2000	0.1138	-0.3420	0.0467	-0.0021	0.1396	-0.0102	-0.0007	-0.2055	0.1759	-0.3959	-0.1071	1.0000	0.2576	-0.0586	-0.1410
IR	0.2375	0.0811	-0.1315	0.1468	0.0793	0.1579	0.0606	-0.1386	-0.1690	0.0282	0.0266	0.1896	0.2576	1.0000	-0.0600	0.1394
UNM	-0.3676	-0.1921	-0.2796	-0.2212	-0.2214	0.1538	-0.0331	-0.0208	-0.3259	-0.0410	0.0167	0.0204	-0.0586	-0.0600	1.0000	-0.0118
USD	-0.0394	-0.0467	0.2245	0.1136	0.1421	0.1938	0.2524	0.1652	0.0685	0.4905	0.1033	0.8886	-0.1410	0.1394	-0.0118	1.0000

Among residuals for sectoral indices, most of the correlations lie between 10%-15% in absolute terms. Also almost all of the correlations have positive sign, indicating that a sector-specific shock has also effects in the same way on other sectors. The two significant sectors which have high correlations with other sectors are MAN and SER. And the highest correlation (0.5713) is between FIN and CON.

Among residuals for macro variables, most of the correlations lie between 0%-10% in absolute terms and they are generally lower than the correlation between residuals of sectoral indices. The highest correlation (0.8886) is between USD and EUR, as expected. The foreign exchange rates have negative correlation with IR, and positive correlation with CRD. The IR has also negative correlation with CPI. Interestingly, the correlation for residuals of GNP has positive correlation with residuals of IR, and negative correlation with residuals of CUR and CPI.

And finally, the correlation between residuals of sectoral indices and macro variables generally lie between 10%-25% in absolute terms.

V. Monte Carlo Simulations

The next step in modeling credit risk is the simulation of losses. In this step, by using our previous empirical models for sectoral indices and macro variables, we generate simulated values of NPL ratios. This Monte Carlo step can be seen as generating 'unconditional loss distribution' for portfolios since there is no restriction (condition) on the evolution of random innovations.

Our framework for loss distribution is a default-mode one. This means that we only consider a loss if a loan goes into default, and losses due to mark-to-market valuation is explicitly excluded. Additionally, by simulating directly losses, we implicitly incorporate the effects of macro variables on both PD and LGD.

In order to find the loss distribution, we first simulate the one-step ahead (next month's) possible NPL ratios. The steps of simulation are described below:

- First the covariance matrix is decomposed into lower and upper triangular matrices by using Cholesky decomposition, such that $\Sigma=AA^T$.
- Then 16 independent random variables are drawn from a standard normal distribution. Z denotes the vector of these random variables.
- These independent random variables are transformed into correlated normal variables by multiplying Z with A, i.e. $Z^*=AZ$.
- The entries of the new vector will be the value of residuals for 8 sectoral indices and 8 ARIMA structures.
- We first forecast the ARIMA structures for macro variables, i.e. we calculate the conditional expectation (conditional mean) of one-step ahead values of macro variables. Then we add the residuals to simulate the new values of macro variables.
- By using simulated values of macro variables obtained in the previous step, and adding the simulated innovations of sectoral indices, the new value of indices (and NPL ratios) are simulated.
- The above steps are done for 20000 times. For each simulation step the new NPL ratios are recorded.

After simulating 20000 times, we have 20000 simulated NPL ratios for 8 sectors. And from this NPL ratios, and *assuming that no new loans are granted within the simulation period (i.e. next month)*, we can calculate the change in credit provisions (i.e. credit losses) as follows:

- Current NPL Ratio is :

$$NPL_t = \frac{NPLTotal_t}{PerformTotal_t + NPLTotal_t}$$

- From this ratio the total non-performing loans *(NPLTotal)* can be derived as:

$$NPLTotal_t = \frac{NPL_t \times PerformTotal_t}{(1 - NPL_t)}$$

- Assuming that no new loans are granted, one period ahead NPL Ratio is :

$$NPL_{t+1} = \frac{NPLTotal_t + \Delta NPLTotal_{t+1}}{PerformTotal_t + NPLTotal_t}$$

- By using the second and third equations, we can derive the change in total NPL as follows:

$$\Delta NPLTotal_{t+1} = PerformTotal_t \times \left[\frac{NPL_{t+1} - NPL_t}{1 - NPL_t} \right]$$

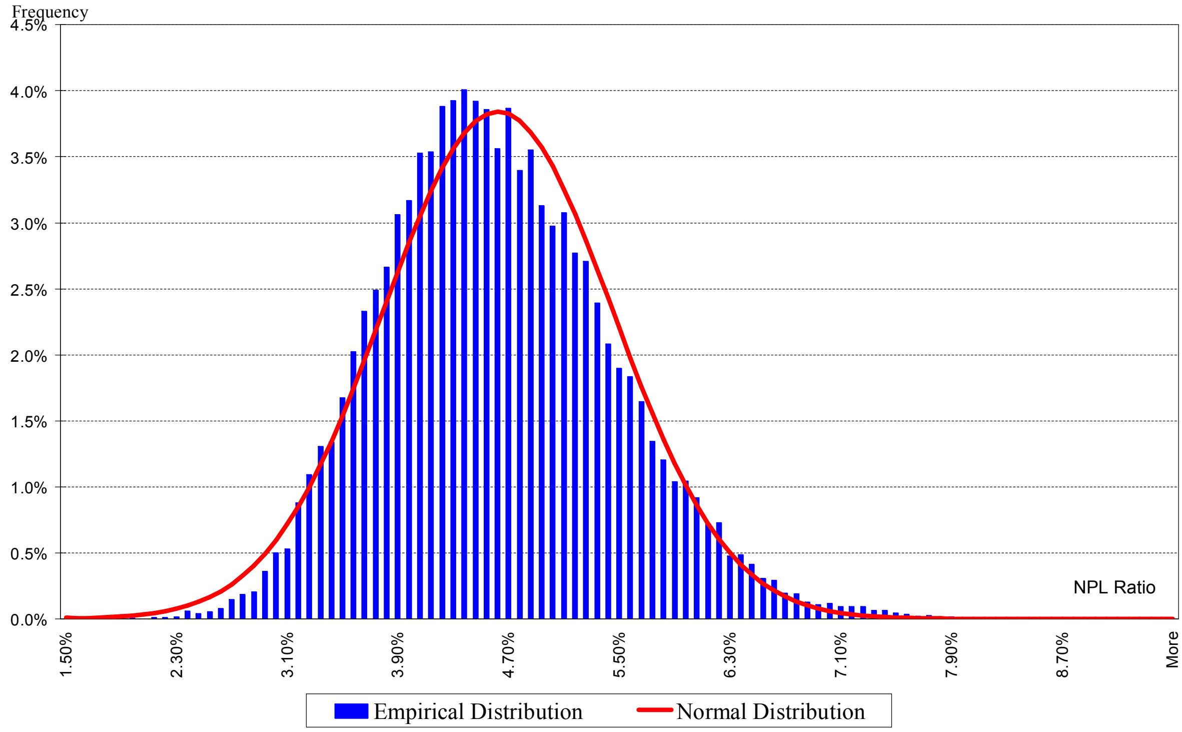
and

$$\frac{\Delta NPLTotal_{t+1}}{PerformTotal_t} = \frac{NPL_{t+1} - NPL_t}{1 - NPL_t} \tag{11}$$

- Given the assumption of no new loans, the last equation gives the change in NPL as a percentage of currently performing loans. This is exactly equal to the percentage of credit losses with respect to the total performing loans.

The NPL ratio and the loss distribution are given in graphs 3 and 4. Detailed results are presented in table 9, in the appendix.

Graph 3: Simulated NPL Ratios (for all sectors)



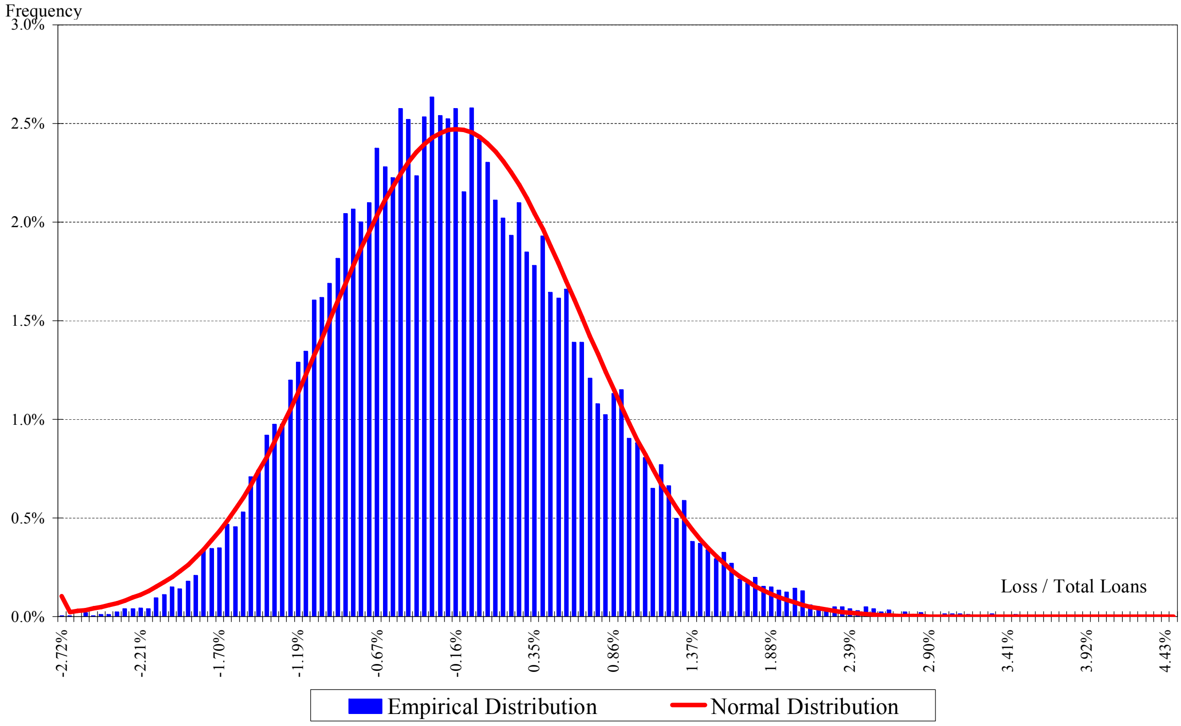
While we assume no new loans, this yields negative losses (returns) when the simulated NPL ratio will be lower than the last in-sample NPL ratio. By this assumption, we implicitly treat the reductions in NPL ratios as if the non-performing loans become performing and the previously incurred provisions are reversed. Additionally, the losses are calculated as the difference between non-performing losses. This also requires a conservative assumption that the new provisions should cover whole value of the loan which becomes non-performing. This assumption is also commensurate with the actual provisioning behavior of Turkish banks, because current provisioning ratio for non-performing loans is near 90%.

The NPL distribution is almost symmetric. The tails of the distribution reaches to near 8%. Although it is more than 1,5 times higher than the current level of NP ratio, it is lower than the NPL ratios in 2001 and 2002.

Since current capital adequacy ratios (CAR) are very high[8], the impacts on CAR levels are relatively small. However, since the magnitude of impacts on CAR depend also on the calculation method of risk-weighted assets, it is more convenient to look at ‘loss/loans’ or ‘loss/capital’ ratios.

[8] As of March 2005, the average capital adequacy ratio is 29.08 %.

Graph 4: Simulated Portfolio Loss Distribution (for all sectors)



The total ‘loss/loans’ ratio exceeds 1.5% in the tails of the distribution and reaches up to 3.5% in the extreme tails. The most significant values are obtained for sectors TRD and OTH. Also the ‘loss/capital’ ratios are approximately twice the ‘loss/loans’ ratios, since the total capital is half the total loan portfolio.

VI. Stress Testing

After performing Monte Carlo simulations, we perform stress testing. Stress testing is an important tool which enables us to see the possible outcome of ‘low probability - high severity events (or tail events)’. In stress testing, one should input some predefined scenarios to the model and estimates the effects of these scenarios. And the most important part of the stress testing is choosing scenarios. There are three common approaches for defining stress scenarios. The first possible scenario includes ‘unit’ change of a variable. For example ‘%1 increase in interest rates’ is an example of this type. This type of stress testing is also called ‘sensitivity analysis’. The second approach defines the scenarios by looking at the dispersion of variables. In this approach, scenarios may be multiples of the standard deviation increase or decrease in the variables. In this approach, if there is a distributional assumption for the variable, we can also attach probabilities for deviations. For example, if we assume normally distributed random variables, we can say that the probability of occurring of a 2-standard deviation or less increase is %48,86. The final approach, which is very common in stress testing financial institutions or portfolios, uses historical worst-case scenarios. In this paper, we apply the last approach since, historical scenarios are actually happened ones.

The approach we use in stress testing is a multivariate one, since we incorporate the correlation structure between innovations. However we do not consider second-round effects between macro variables. Additionally, our approach is an aggregated model since we do not analyze the potential effects of stress scenarios on individual bank’s balance sheets, and ignore the second-round effects related to individual bank's fragility. It is also important to note that, the model does capture only the systematic component of the default process and the idiosynatric part is assumed to be eliminated through portfolio diversification.

In order to use historical worst-case scenarios, we first find the extreme residuals from the ARIMA equations for macro variables[9]. Then these residuals are standardized by dividing their variances. And finally these standardized residuals are replaced with the corresponding standard normal random variables in vector Z defined in previous section. The standardized residuals and their standard normal probabilities are given in table 8.

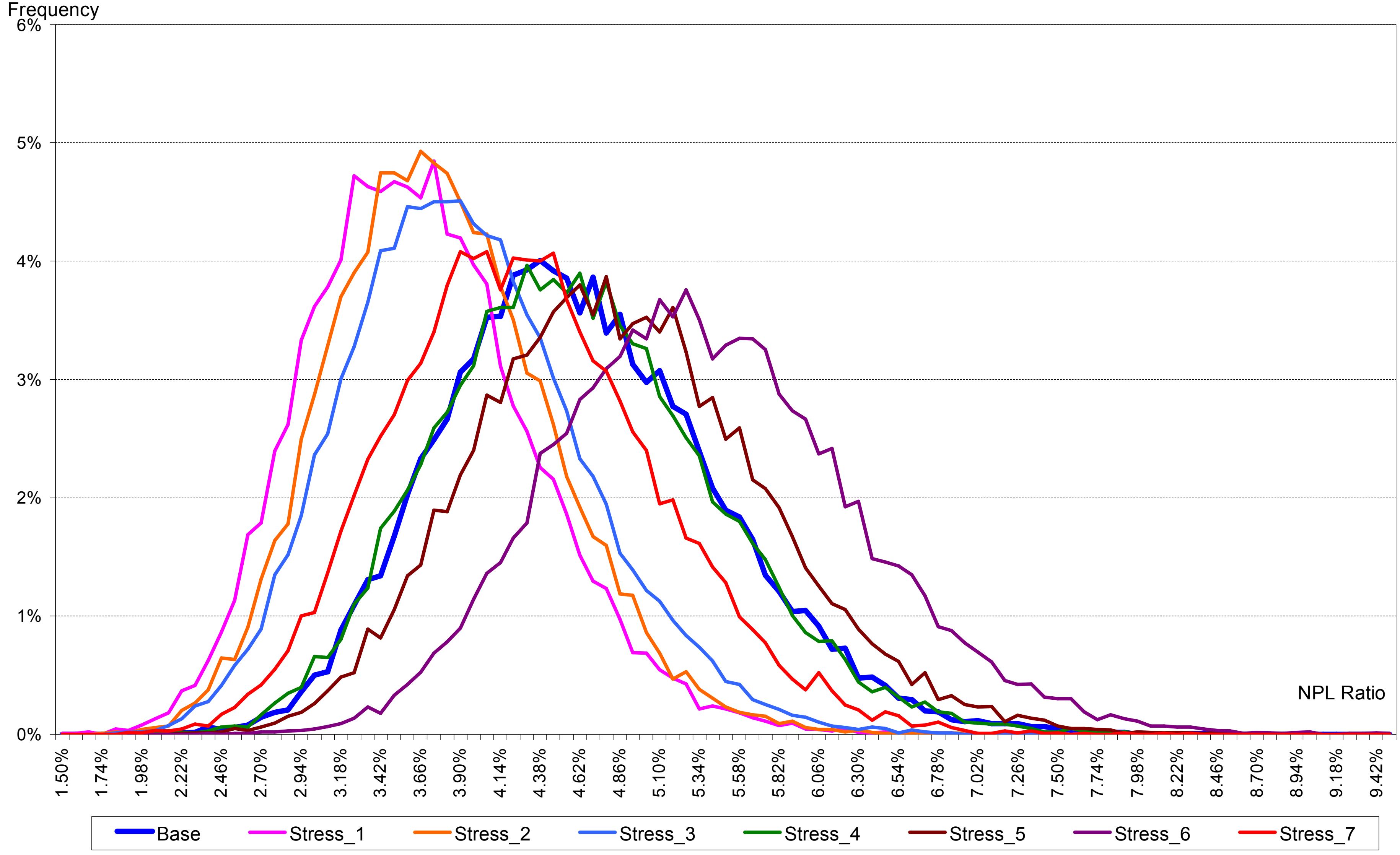
Table 8: Standardized Residuals and Their Standard Normal Probabilities

Scenario No	Macro Variable	Standardized Residual	Standard Normal Probability
1	CUR	-3.45	0.02854%
2	CPI	-2.75	0.29376%
3	CRD	2.90	0.18882%
4	USD	-2.99	0.14130%
5	GNP	-3.84	0.00617%
6	IR	8.84	0.00000%
7	UNM	5.12	0.00002%

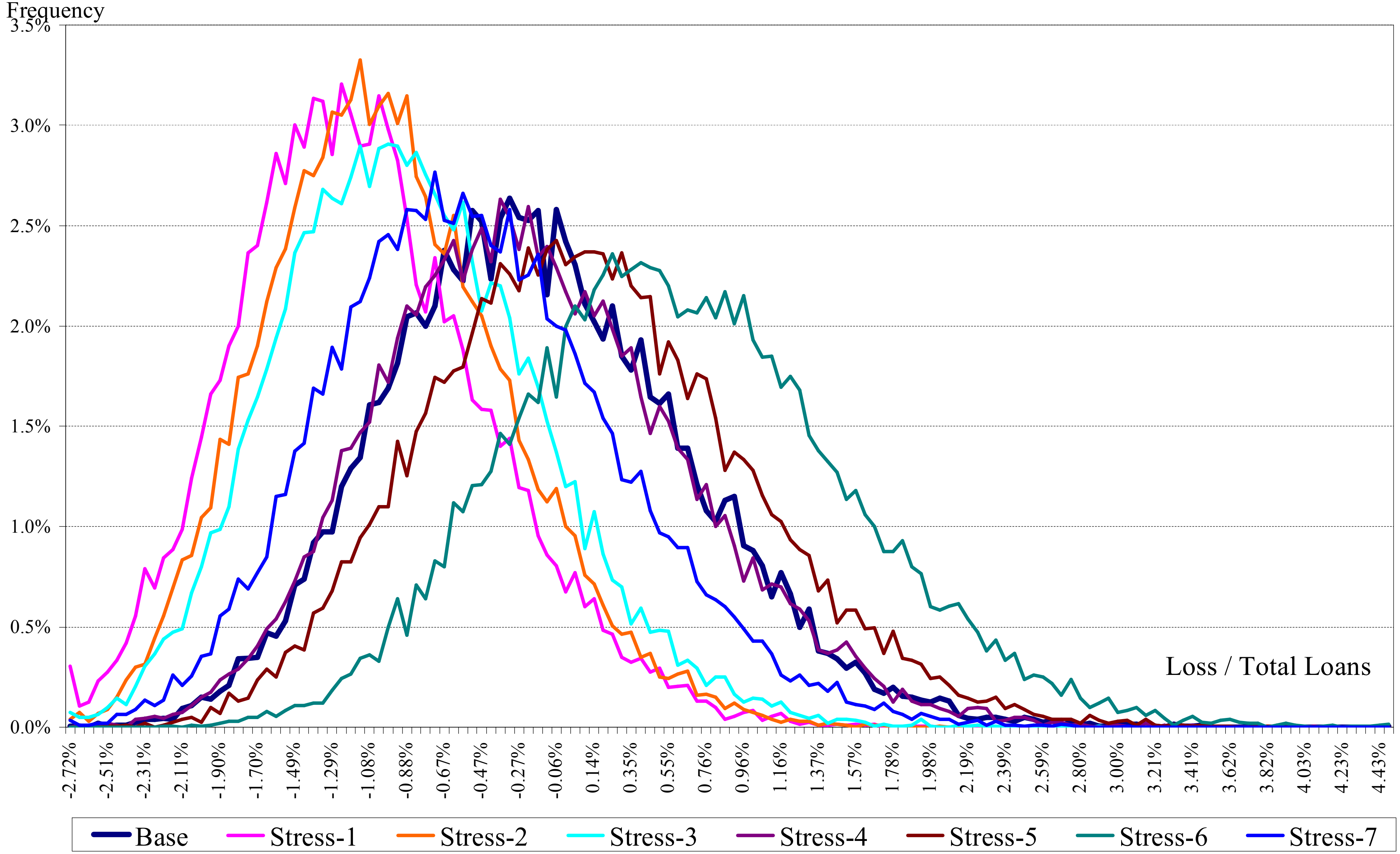
These standardized residuals are multiplied with the decomposed covariance matrix and 20000 simulations are generated for macro variables and sectoral indices. However, in some cases, historical worst-case values for some variables do not generate bad outcomes for the entire model. This is because of the correlation structure between variables. For example, a bad outcome for one variable may also generate a good for another variable, and the final result may be better than the base scenario. Therefore, an extremely bad scenario for an individual variable may be a good scenario for the entire set of variables. The results of the stress tests are presented in graphs 5 and 6. Detailed results are presented in tables 10 and 11, in the appendix. The 'base scenarios' in the tables and graphs represents the scenarios we generated in the previous section.

[9] Since the sign of EUR is positive for two equations and negative for one equation, we do not include a stress scenario fort his variable.

Graph 5: NPL Ratios for Stress Scenarios (All Sectors)



Graph 6: Loss Distributions for Stress Scenarios (All Sectors)



The results of the stress testing can be seen as the ‘conditional distributions” of NPL ratios and losses, since we manually input the innovation of one macro variable in each scenario. However, as explained above, these scenarios may not represent the ‘worst cases’ for the entire model. They are only ‘single-factor shocks’ applied to the model.

When we compare the results of stress scenarios with base scenario, we see more skewed distributions for NPL ratios. However distributions are skewed to left for some scenarios and skewed to right for some other scenarios, because of the reasons explained above. The same skewness property also appears in the loss distributions. Among all scenarios, the scenario for USD yields losses very close to the base scenario. And only the scenarios for GNP and IR yields higher losses than the base scenario. This seems interesting since GNP and IR appears in only one regression equation for sectoral indices. This shows the effects of these two variables over other variables among covariance structure. Also the magnitude of shocks is one of the causes of this result.

The simulation results suggest mean NPL ratios around 3.5%-5.5% and the 99th percentile[10] NPL ratios reach to 7.65%. The conditional loss distributions generally have negative means, indicating profit rather than loss. And 99th percentile losses exceed 2% in some scenarios. The loss/capital ratios are twice the loss/loans ratios and reaches to 5.7% in scenario 6. The effects of losses on CAR are very limited, since the current levels are very high. The decreases in CAR do not exceed 1.2 percentage points for 99th percentile levels, and do not exceed 1.6 percentage points for 99.99th percentile levels.

In absorbing losses, there are three main sources of cushion: provisions, profit margins and allocated capital. Banks charge a provision for each loan against its expected loss. This provision is already included in the profit margins. If additional losses occur in some parts of the portfolio, the return from remaining parts can also be used for offsetting these losses. And in the extreme case, if losses exceed the whole profit margin, the capital allocated to that portfolio absorbs the losses.

The assessment of risk bearing capacity for Turkish banking system requires additional assumptions for returns from loans and allocated capital. The assumptions used are explained below:

- If some loans go into default, remaining loans are assumed to generate profit as if we are in normal times. This means that the shocks we apply do not change the return potential of performing loans. This figure is approximated by average return-on-assets (ROA) values for all assets. As of March 2005, the ROA is 1% for the entire quarter (see BRSA 2005a). Therefore the monthly return for loan portfolio is assumed to be 0.33%. Since this figure already includes provisions, we do not add provisions in our analysis.
- Average risk weight for loans is calculated as 84.11%[11]. This means that the capital allocated to loan portfolio is 6.73%[12]. Capital is a stock variable. Therefore it can be used to absorb the losses that occur in any time.
- Since current CAR is 29.08%, this means that the buffer capital is 2.64[13] times the required capital. The assumption for this capital is important. If we assume that this capital is held against risks that are not covered by current regulations, we can not add a buffer capital

[10] 99th percentile represents an event that may occur every 100 months (~8 years). And 99,99th percentile represents an event that may occur every 1000 months (~83 years).
[11] Calculation is done based on data published in BRSA (2005a and 2005b).
[12] 84.11% x 8% = 6.73%
[13] (29.08% - 8%) / 8% = 2.64

for loan portfolio. Otherwise, if we assume that all or a part of this capital is held because of the weaknesses of the current regulation[14], we can add all or a part of it to the capital held for loan portfolio.

- Therefore, for absorbing losses occur in one month period, we have 0.33% profits and 6.73% of capital, and potentially a buffer capital.

When we compare the losses with the above cushions, we see that even in the extreme tails (i.e. 99th and 99.99th percentiles), the losses do not exceed the cushions. Therefore *under our strict assumptions*, we can say that the Turkish banking system can absorb very extreme losses for its loan portfolio, if a single-factor shock occurs in a one-month period.

VII. CONCLUSION

The assessment of banking sectors' vulnerabilities to credit losses is one of the most important issues for supervisors and other related parties. CPV model developed by Wilson (1997a and 1997b) is one of the most useful approaches for evaluating systemic and macroeconomic aspects of credit risk. In this paper, a revised version CPV is applied to sectoral NPL ratios of Turkish banking system. We used a logistic transformation for NPL ratios and, using OLS, estimate a structural model including macro variables as explanatory variables. Also the evolutions of the macro variables are estimated by ARIMA models. Then by using the covariance structure of the entire model, a Monte Carlo simulation was done to simulate one-step-ahead NPL ratios and credit losses were calculated. Also we perform stress tests for each macro variable. Finally the expected and unexpected losses are calculated from the loss distribution.

Our estimation results show that most of the changes in NPL ratios, and therefore credit losses, can be explained by using macroeconomic variables. The dependence level and the explanatory macro variables may change for different sectors. But the sectoral credit risks are related to each other through co-dependence on macro variables, as well as the correlation between these variables. Under our strict assumptions, the Monte Carlo simulations and the stress tests suggests loss levels which can be absorbed by profits and allocated capital.

The model established in this study has some limitations. The improvements in these limitations can enhance the forecast capacity of the model in the future. The first set of limitations comes from the lack and/or inadequacy of some data. For example, if default rates are used, rather than NPL ratios, the model can be enhanced. Or by using large number of observations (which are not available today), the model may have a better forecast capacity. In future research, some other macro variables may be tested for their explanatory power. Also for the evolution of macro variables, it is possible to use other techniques to incorporate second-round effects.

Beside its limitations, the model can also be extended for several different purposes. For example, the implied correlations between sectoral default rates can be derived from the model, or multi-step ahead forecasts can be performed with a more general model. Additionally, the model can be used to analyze and calibrate the Basel-II requirements. For example, the credit losses obtained from the model can be compared with the Basel-II requirements, or the procyclicality effects of Basel-II can be analyzed by using the model.

[14] In Turkey, current capital adequacy regulation is mainly based on Basel-I rules which attracts severe criticism regarding its capacity to capture the riskiness of the positions.

APPENDIX

Table 9: Monte Carlo Simulation Results

NPL Ratios for Base Scenario

	AGR	CON	ENG	FIN	MAN	SER	TRD	OTH	TOTAL
mean	4.99%	4.84%	0.85%	1.76%	6.01%	4.20%	4.22%	3.66%	4.58%
stdev	1.00%	1.10%	0.24%	0.85%	1.16%	1.08%	1.82%	1.55%	0.83%
50.000%	4.94%	4.76%	0.82%	1.62%	5.95%	4.11%	3.98%	3.44%	4.52%
75.000%	5.64%	5.54%	0.99%	2.23%	6.74%	4.88%	5.28%	4.56%	5.12%
90.000%	6.31%	6.29%	1.17%	2.92%	7.55%	5.63%	6.64%	5.75%	5.68%
95.000%	6.73%	6.78%	1.28%	3.38%	8.01%	6.10%	7.58%	6.56%	6.04%
97.500%	7.11%	7.22%	1.39%	3.80%	8.44%	6.55%	8.47%	7.25%	6.35%
99.000%	7.53%	7.71%	1.52%	4.30%	8.98%	7.06%	9.50%	8.15%	6.75%
99.500%	7.92%	8.09%	1.59%	4.78%	9.33%	7.43%	10.21%	8.70%	7.08%
99.750%	8.17%	8.42%	1.69%	5.23%	9.67%	7.80%	10.95%	9.34%	7.32%
99.900%	8.56%	8.85%	1.80%	5.59%	10.09%	8.30%	11.67%	9.94%	7.53%
99.950%	8.76%	9.18%	1.88%	5.92%	10.25%	8.70%	12.06%	10.36%	7.69%
99.975%	9.15%	9.34%	1.95%	6.32%	10.44%	8.96%	12.39%	10.64%	7.81%
99.990%	9.31%	9.84%	2.07%	6.71%	10.58%	9.15%	13.21%	11.67%	7.85%

Loss/Loans Ratios for Base Scenario

	AGR	CON	ENG	FIN	MAN	SER	TRD	OTH	TOTAL
mean	0.11%	-0.31%	-0.07%	-0.13%	-0.04%	-0.43%	-1.11%	0.12%	-0.19%
stdev	1.00%	1.10%	0.24%	0.85%	1.16%	1.07%	1.80%	1.55%	0.82%
50.000%	0.06%	-0.38%	-0.09%	-0.27%	-0.11%	-0.51%	-1.36%	-0.09%	-0.24%
75.000%	0.74%	0.41%	0.08%	0.34%	0.69%	0.25%	-0.06%	1.02%	0.35%
90.000%	1.42%	1.12%	0.25%	1.01%	1.48%	0.98%	1.30%	2.21%	0.90%
95.000%	1.84%	1.61%	0.37%	1.48%	1.99%	1.45%	2.25%	2.96%	1.23%
97.500%	2.24%	2.00%	0.48%	1.92%	2.41%	1.89%	3.12%	3.70%	1.54%
99.000%	2.70%	2.51%	0.62%	2.49%	2.93%	2.42%	4.19%	4.54%	1.95%
99.500%	3.07%	2.91%	0.71%	2.88%	3.30%	2.76%	4.84%	5.14%	2.23%
99.750%	3.36%	3.23%	0.78%	3.32%	3.62%	3.15%	5.44%	5.74%	2.51%
99.900%	3.72%	3.62%	0.90%	3.82%	4.13%	3.54%	6.12%	6.81%	2.94%
99.950%	4.01%	3.94%	1.00%	4.16%	4.47%	3.84%	6.47%	7.55%	3.14%
99.975%	4.22%	4.04%	1.07%	4.69%	4.57%	4.08%	7.19%	7.97%	3.31%
99.990%	4.54%	4.22%	1.15%	5.03%	5.05%	4.44%	8.06%	8.75%	3.43%

Loss/Capital Ratios for Base Scenario

	AGR	CON	ENG	FIN	MAN	SER	TRD	OTH	TOTAL
mean	0.01%	-0.04%	-0.01%	-0.02%	-0.04%	-0.04%	-0.26%	0.04%	-0.37%
stdev	0.09%	0.13%	0.04%	0.10%	1.00%	0.10%	0.42%	0.47%	1.63%
50.000%	0.01%	-0.04%	-0.01%	-0.03%	-0.09%	-0.05%	-0.32%	-0.03%	-0.47%
75.000%	0.07%	0.05%	0.01%	0.04%	0.60%	0.02%	-0.01%	0.31%	0.69%
90.000%	0.13%	0.13%	0.04%	0.12%	1.28%	0.10%	0.30%	0.66%	1.78%
95.000%	0.17%	0.19%	0.06%	0.18%	1.72%	0.14%	0.52%	0.89%	2.43%
97.500%	0.21%	0.24%	0.07%	0.23%	2.08%	0.19%	0.73%	1.11%	3.05%
99.000%	0.25%	0.30%	0.09%	0.30%	2.54%	0.24%	0.98%	1.36%	3.85%
99.500%	0.28%	0.34%	0.11%	0.35%	2.86%	0.27%	1.13%	1.55%	4.40%
99.750%	0.31%	0.38%	0.12%	0.40%	3.13%	0.31%	1.27%	1.73%	4.97%
99.900%	0.34%	0.43%	0.14%	0.46%	3.56%	0.35%	1.43%	2.05%	5.81%
99.950%	0.37%	0.47%	0.15%	0.50%	3.86%	0.38%	1.51%	2.27%	6.21%
99.975%	0.39%	0.48%	0.16%	0.56%	3.95%	0.40%	1.68%	2.40%	6.54%
99.990%	0.42%	0.50%	0.17%	0.60%	4.36%	0.44%	1.88%	2.63%	6.79%

Capital Adequacy Ratios for Base Scenario

	AGR	CON	ENG	FIN	MAN	SER	TRD	OTH	TOTAL
mean	29.08%	29.09%	29.08%	29.08%	29.09%	29.09%	29.13%	29.07%	29.16%
stdev	29.06%	29.05%	29.07%	29.06%	28.87%	29.06%	28.99%	28.98%	28.74%
50.000%	29.08%	29.09%	29.08%	29.09%	29.10%	29.09%	29.15%	29.09%	29.18%
75.000%	29.07%	29.07%	29.08%	29.07%	28.96%	29.08%	29.08%	29.02%	28.94%
90.000%	29.05%	29.05%	29.07%	29.06%	28.82%	29.06%	29.02%	28.94%	28.71%
95.000%	29.05%	29.04%	29.07%	29.04%	28.73%	29.05%	28.97%	28.90%	28.58%
97.500%	29.04%	29.03%	29.07%	29.03%	28.65%	29.04%	28.93%	28.85%	28.45%
99.000%	29.03%	29.02%	29.06%	29.02%	28.55%	29.03%	28.88%	28.80%	28.28%
99.500%	29.02%	29.01%	29.06%	29.01%	28.49%	29.03%	28.85%	28.76%	28.16%
99.750%	29.02%	29.00%	29.06%	29.00%	28.43%	29.02%	28.82%	28.72%	28.04%
99.900%	29.01%	28.99%	29.05%	28.99%	28.34%	29.01%	28.79%	28.66%	27.86%
99.950%	29.00%	28.98%	29.05%	28.98%	28.28%	29.00%	28.77%	28.61%	27.78%
99.975%	29.00%	28.98%	29.05%	28.96%	28.26%	29.00%	28.73%	28.58%	27.71%
99.990%	28.99%	28.98%	29.05%	28.96%	28.17%	28.99%	28.69%	28.53%	27.65%

Note: As of March 2005, total capital is 45.265.000 YTL, total risk-weighted assets is 155.651.000 YTL and average capital adequacy ratio is 29,08%.

Table 10: NPL Ratios and (Loss/Total Loans) Ratios for Different Stress Scenarios

Mean NPL Ratios

Sector	Base	Stress-1	Stress-2	Stress-3	Stress-4	Stress-5	Stress-6	Stress-7
AGR	4.99%	3.06%	4.54%	4.61%	4.99%	4.82%	4.99%	4.99%
CON	4.84%	4.72%	4.63%	4.82%	4.56%	4.78%	4.81%	4.28%
ENG	0.85%	0.79%	1.01%	0.84%	0.84%	0.87%	0.60%	0.73%
FIN	1.76%	1.84%	1.31%	1.37%	1.75%	1.75%	1.76%	1.76%
MAN	6.01%	4.32%	4.69%	4.95%	6.01%	6.08%	6.64%	5.70%
SER	4.20%	3.41%	4.27%	4.09%	4.03%	4.38%	4.03%	3.97%
TRD	4.22%	4.29%	3.86%	3.21%	4.22%	4.57%	8.25%	3.56%
OTH	3.66%	3.01%	2.54%	3.22%	3.67%	4.84%	3.89%	3.21%
TOTAL	4.58%	3.62%	3.75%	3.88%	4.56%	4.83%	5.34%	4.25%

Mean for (Loss/Total Loans)

Sector	Base	Stress-1	Stress-2	Stress-3	Stress-4	Stress-5	Stress-6	Stress-7
AGR	0.11%	-1.81%	-0.34%	-0.28%	0.10%	-0.05%	0.12%	0.11%
CON	-0.31%	-0.42%	-0.51%	-0.32%	-0.59%	-0.35%	-0.32%	-0.87%
ENG	-0.07%	-0.12%	0.10%	-0.07%	-0.07%	-0.05%	-0.32%	-0.19%
FIN	-0.13%	-0.01%	-0.56%	-0.50%	-0.12%	-0.12%	-0.11%	-0.12%
MAN	-0.04%	-1.73%	-1.37%	-1.12%	-0.06%	0.03%	0.59%	-0.36%
SER	-0.43%	-1.23%	-0.35%	-0.55%	-0.60%	-0.25%	-0.60%	-0.68%
TRD	-1.11%	-1.02%	-1.44%	-2.10%	-1.09%	-0.77%	2.94%	-1.78%
OTH	0.12%	-0.54%	-1.02%	-0.35%	0.12%	1.29%	0.36%	-0.35%
TOTAL	-0.19%	-1.15%	-1.01%	-0.89%	-0.21%	0.08%	0.59%	-0.53%

99th Percentile for NPL Ratios

Sector	Base	Stress-1	Stress-2	Stress-3	Stress-4	Stress-5	Stress-6	Stress-7
AGR	7.53%	4.56%	6.99%	7.01%	7.59%	7.43%	7.60%	7.60%
CON	7.71%	7.59%	7.42%	7.75%	7.40%	7.66%	7.69%	6.94%
ENG	1.52%	1.44%	1.75%	1.52%	1.52%	1.56%	1.11%	1.32%
FIN	4.30%	4.56%	3.48%	3.55%	4.42%	4.33%	4.38%	4.31%
MAN	8.98%	6.56%	7.02%	7.46%	9.00%	9.04%	9.75%	8.56%
SER	7.06%	5.87%	7.14%	6.87%	6.76%	7.28%	6.90%	6.69%
TRD	9.50%	9.39%	8.72%	7.56%	9.47%	9.95%	14.66%	8.41%
OTH	8.15%	7.01%	6.00%	7.33%	8.05%	9.81%	8.58%	7.31%
TOTAL	6.75%	5.44%	5.49%	5.74%	6.71%	7.06%	7.65%	6.26%

99th Percentile for (Loss/Total Loans)

Sector	Base	Stress-1	Stress-2	Stress-3	Stress-4	Stress-5	Stress-6	Stress-7
AGR	2.70%	-0.32%	2.08%	2.16%	2.67%	2.55%	2.70%	2.68%
CON	2.51%	2.42%	2.30%	2.58%	2.25%	2.55%	2.52%	1.80%
ENG	0.62%	0.53%	0.84%	0.60%	0.62%	0.63%	0.21%	0.41%
FIN	2.49%	2.68%	1.54%	1.73%	2.42%	2.53%	2.52%	2.50%
MAN	2.93%	0.43%	0.95%	1.42%	2.87%	2.98%	3.69%	2.49%
SER	2.42%	1.21%	2.48%	2.22%	2.20%	2.67%	2.24%	2.03%
TRD	4.19%	4.17%	3.50%	2.33%	4.05%	4.57%	9.49%	2.92%
OTH	4.54%	3.44%	2.45%	3.82%	4.58%	6.28%	5.01%	3.80%
TOTAL	1.95%	0.64%	0.71%	0.98%	1.94%	2.30%	2.88%	1.53%

99,9th Percentile for NPL Ratios

Sector	Base	Stress-1	Stress-2	Stress-3	Stress-4	Stress-5	Stress-6	Stress-7
AGR	8.56%	5.18%	7.96%	7.89%	8.67%	8.45%	8.60%	8.66%
CON	8.85%	8.71%	8.42%	8.90%	8.54%	8.80%	8.72%	7.95%
ENG	1.80%	1.72%	2.14%	1.78%	1.81%	1.88%	1.37%	1.57%
FIN	5.59%	5.76%	4.68%	4.71%	5.76%	5.97%	5.88%	5.56%
MAN	10.09%	7.50%	7.91%	8.59%	10.03%	10.23%	10.72%	9.46%
SER	8.30%	6.87%	8.18%	8.01%	7.92%	8.26%	8.09%	7.73%
TRD	11.67%	11.47%	11.06%	9.70%	11.32%	11.63%	16.99%	10.61%
OTH	9.94%	9.05%	7.68%	9.15%	10.19%	11.86%	10.68%	8.98%
TOTAL	7.53%	6.20%	6.22%	6.43%	7.53%	7.89%	8.51%	7.04%

99,9th Percentile for (Loss/Total Loans)

Sector	Base	Stress-1	Stress-2	Stress-3	Stress-4	Stress-5	Stress-6	Stress-7
AGR	3.72%	0.19%	3.10%	3.12%	3.59%	3.44%	3.64%	3.66%
CON	3.62%	3.50%	3.47%	3.89%	3.34%	3.47%	3.55%	2.87%
ENG	0.90%	0.81%	1.18%	0.90%	0.91%	0.89%	0.42%	0.68%
FIN	3.82%	3.89%	2.74%	3.14%	3.68%	3.86%	3.93%	3.87%
MAN	4.13%	1.27%	1.90%	2.42%	4.02%	4.11%	4.70%	3.68%
SER	3.54%	2.10%	3.44%	3.25%	3.42%	3.94%	3.31%	3.12%
TRD	6.12%	6.64%	5.80%	4.25%	6.44%	7.40%	11.78%	4.78%
OTH	6.81%	5.14%	4.18%	5.70%	6.40%	8.23%	7.18%	5.71%
TOTAL	2.94%	1.30%	1.37%	1.80%	2.75%	3.15%	3.75%	2.30%

Table 11: (Loss/Total Capital) Ratios and Capital Adequacy Ratios for Different Stress Scenarios

Mean (Loss/Total Capital)

Sector	Base	Stress-1	Stress-2	Stress-3	Stress-4	Stress-5	Stress-6	Stress-7
AGR	0.01%	-0.17%	-0.03%	-0.03%	0.01%	0.00%	0.01%	0.01%
CON	-0.04%	-0.05%	-0.06%	-0.04%	-0.07%	-0.04%	-0.04%	-0.10%
ENG	-0.01%	-0.02%	0.02%	-0.01%	-0.01%	-0.01%	-0.05%	-0.03%
FIN	-0.02%	0.00%	-0.07%	-0.06%	-0.01%	-0.01%	-0.01%	-0.01%
MAN	-0.04%	-1.50%	-1.18%	-0.97%	-0.05%	0.02%	0.51%	-0.31%
SER	-0.04%	-0.12%	-0.03%	-0.05%	-0.06%	-0.02%	-0.06%	-0.07%
TRD	-0.26%	-0.24%	-0.34%	-0.49%	-0.25%	-0.18%	0.68%	-0.42%
OTH	0.04%	-0.16%	-0.31%	-0.11%	0.04%	0.39%	0.11%	-0.11%
TOTAL	-0.37%	-2.27%	-2.01%	-1.75%	-0.42%	0.16%	1.16%	-1.04%

Mean Capital Adequacy Ratio

Sector	Base	Stress-1	Stress-2	Stress-3	Stress-4	Stress-5	Stress-6	Stress-7
AGR	29.08%	29.12%	29.09%	29.09%	29.08%	29.08%	29.08%	29.08%
CON	29.09%	29.09%	29.09%	29.09%	29.10%	29.09%	29.09%	29.10%
ENG	29.08%	29.08%	29.08%	29.08%	29.08%	29.08%	29.09%	29.09%
FIN	29.08%	29.08%	29.09%	29.09%	29.08%	29.08%	29.08%	29.08%
MAN	29.09%	29.39%	29.32%	29.28%	29.09%	29.08%	28.98%	29.14%
SER	29.09%	29.11%	29.09%	29.09%	29.09%	29.09%	29.09%	29.09%
TRD	29.13%	29.13%	29.15%	29.18%	29.13%	29.12%	28.94%	29.17%
OTH	29.07%	29.11%	29.14%	29.10%	29.07%	29.00%	29.06%	29.10%
TOTAL	29.16%	29.55%	29.49%	29.44%	29.17%	29.05%	28.84%	29.30%

99th Percentile for (Loss/Total Capital)

Sector	Base	Stress-1	Stress-2	Stress-3	Stress-4	Stress-5	Stress-6	Stress-7
AGR	0.25%	-0.03%	0.19%	0.20%	0.25%	0.24%	0.25%	0.25%
CON	0.30%	0.29%	0.27%	0.31%	0.27%	0.30%	0.30%	0.21%
ENG	0.09%	0.08%	0.13%	0.09%	0.09%	0.09%	0.03%	0.06%
FIN	0.30%	0.32%	0.18%	0.21%	0.29%	0.30%	0.30%	0.30%
MAN	2.54%	0.37%	0.82%	1.23%	2.48%	2.57%	3.18%	2.15%
SER	0.24%	0.12%	0.24%	0.22%	0.22%	0.26%	0.22%	0.20%
TRD	0.98%	0.97%	0.82%	0.54%	0.95%	1.07%	2.22%	0.68%
OTH	1.36%	1.04%	0.74%	1.15%	1.38%	1.89%	1.51%	1.14%
TOTAL	3.85%	1.27%	1.41%	1.93%	3.83%	4.56%	5.70%	3.02%

99th Percentile for Capital Adequacy Ratio

Sector	Base	Stress-1	Stress-2	Stress-3	Stress-4	Stress-5	Stress-6	Stress-7
AGR	29.03%	29.09%	29.04%	29.04%	29.03%	29.03%	29.03%	29.03%
CON	29.02%	29.02%	29.02%	29.02%	29.03%	29.02%	29.02%	29.04%
ENG	29.06%	29.06%	29.05%	29.06%	29.06%	29.06%	29.07%	29.07%
FIN	29.02%	29.01%	29.04%	29.04%	29.02%	29.02%	29.02%	29.02%
MAN	28.55%	29.00%	28.91%	28.83%	28.57%	28.55%	28.42%	28.64%
SER	29.03%	29.06%	29.03%	29.04%	29.04%	29.03%	29.04%	29.04%
TRD	28.88%	28.88%	28.91%	28.97%	28.89%	28.86%	28.62%	28.94%
OTH	28.80%	28.87%	28.93%	28.84%	28.80%	28.69%	28.77%	28.84%
TOTAL	28.28%	28.82%	28.79%	28.68%	28.28%	28.13%	27.89%	28.45%

99,9th Percentile for (Loss/Total Capital)

Sector	Base	Stress-1	Stress-2	Stress-3	Stress-4	Stress-5	Stress-6	Stress-7
AGR	0.34%	0.02%	0.29%	0.29%	0.33%	0.32%	0.34%	0.34%
CON	0.43%	0.41%	0.41%	0.46%	0.40%	0.41%	0.42%	0.34%
ENG	0.14%	0.12%	0.18%	0.14%	0.14%	0.14%	0.06%	0.10%
FIN	0.46%	0.47%	0.33%	0.38%	0.44%	0.46%	0.47%	0.47%
MAN	3.56%	1.10%	1.65%	2.09%	3.47%	3.55%	4.06%	3.18%
SER	0.35%	0.21%	0.34%	0.32%	0.34%	0.39%	0.32%	0.31%
TRD	1.43%	1.55%	1.35%	0.99%	1.50%	1.73%	2.75%	1.11%
OTH	2.05%	1.54%	1.26%	1.71%	1.92%	2.47%	2.16%	1.72%
TOTAL	5.81%	2.57%	2.71%	3.57%	5.44%	6.23%	7.43%	4.55%

99,9th Percentile for Capital Adequacy Ratio

Sector	Base	Stress-1	Stress-2	Stress-3	Stress-4	Stress-5	Stress-6	Stress-7
AGR	29.01%	29.08%	29.02%	29.02%	29.01%	29.02%	29.01%	29.01%
CON	28.99%	29.00%	29.00%	28.99%	29.00%	29.00%	28.99%	29.01%
ENG	29.05%	29.06%	29.04%	29.05%	29.05%	29.05%	29.07%	29.06%
FIN	28.99%	28.98%	29.01%	29.00%	28.99%	28.99%	28.98%	28.99%
MAN	28.34%	28.85%	28.74%	28.65%	28.36%	28.34%	28.23%	28.42%
SER	29.01%	29.04%	29.01%	29.02%	29.01%	29.00%	29.01%	29.02%
TRD	28.79%	28.76%	28.80%	28.88%	28.77%	28.72%	28.51%	28.85%
OTH	28.66%	28.76%	28.82%	28.73%	28.68%	28.57%	28.63%	28.73%
TOTAL	27.86%	28.55%	28.52%	28.34%	27.94%	27.77%	27.52%	28.13%

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