MACRO STRESS-TESTING APPROACH OF CREDIT RISK:

EVIDENCE FROM TURKEY

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Thesis Abstract

Ali Yavuz Polat, “Macro Stress-Testing Approach of Credit Risk: Turkish Case”

There is a vast literature on financial stability issue after the onset of the recent global financial crises. Stress-testing, which can be defined as the techniques used by policy makers to assess the vulnerability of the financial system to extreme events is one of the key issues in financial stability literature. The basic idea behind stress-testing is finding a risk proxy for financial stability and performing impulse response and sensitivity analysis on this proxy. There are different risk measures used in the literature such as; credit risk, market risk (FX risk etc.), liquidity risk, and contagion risk. In this study, we choose to analyze credit risk and use Non-performing loan (NPL) ratio as a proxy for the credit risk. The reason we focus on the credit risk is the financial structure of the Turkish economy. The main players in giving loans are conventional banks. Thus we think that NPL ratio will be a good proxy for assessing banks fragility and consequently financial sector stability. There is no published study on macro stress testing for Turkish case. Therefore, this study as a first attempt for macro-stress testing applied on Turkish economy opens a window for further studies. Also this thesis is one of the first studies, revealing the determinant of Non-Performing Loans after the 2000-2001 period.

Using a 7-lag VAR model, we performed dynamic out of forecasts which reveals quite accurate results compared with the actual data. Since forecasting is a very crucial tool for both policy makers and market players, these results are one of the main strengths and contributions of this study, Also policy recommendations are provided in accordance with the robust findings. Firstly, industry production used as a proxy for GDP has a significant effect on NPL ratio, which can give prediction insights to the policy makers depending on the real state of the economy. Secondly, capacity usage has a significant positive effect on NPL ratio which conflicts with the prior expectations. Therefore policy maker should be concerned about the discrepancy between real stimulus in the economy and people’s expectations. Lastly, spread used as a proxy for the expectation of banks reveals quite useful insights about the expectations o the market.

Tez Özeti

Ali Yavuz Polat, "Kredi Riskine Makro-Stres Testi Yaklaşımı : Türkiye Örneği"

Son yaşanan küresel krizden sonra finansal sağlamlık üzerine yapılan çok fazla çalışma vardır. Finansal sistemin olağanüstü durumlara olan hassasiyeti olarak tanınlayabileceğimiz stres testi bu çalışmaların önemli alanlarından bir tanesi olarak karşımıza çıkmaktadır. Stres testinin temel mantığı finansal sağlamlık için bir gösterge bulup bu gösterge üzerine etki tepki ve hassasiyet analizleri uygulamaktır. Literaturde farklı risk ölçümleri vardır. Bunlar; kredi riski, market riski, likidite riski ve bulaşma riski olarak sınıflandırılabilir. Bu tezde biz kredi riski üzerine yoğunlaştık ve "Donuk Kredileri (NPL)" kredi riskinin göstergesi olarak kullandık. Kredi riski üzerine yoğunlaşmamızın nedeni Türkiye ekonomisinin finansal yapısıdır. Finansal sistemdeki temel oyuncular kredi veren klasik bankalardır. Bu yüzden donuk kredilerin bankacılık sistemin kırılganlığını ölçmede ve dolayısıyla finansal sistemin sağlamlığını ölçmede iyi bir gösterge olduğunu düşündük. Daha önceden Türk ekonomisine macro stress testi uygulayan basılmış ya da yayınlanmış bir çalışma olmadığını göz önüne aldığımızda, bu çalışma Türkiye üzerine yapılan ilk makro stres testi uygulaması olması açısından ileriki çalışmalara kapı aralayacaktır. Ayrıca bu çalışma 2000-2001 krizi sonrası Donuk Kredilerin (NPL) belirleyicilerini gösteren ilk çalışma olması açısından da önemlidir.

7 periodlu VAR modeli kullanarak dinamik örneklem dışı tahmini yaptık ve bu tahmini gerçek veri ile karşılaştırdığımızda gayet yüksek isabet oranı elde ettiğimizi gördük. Politika yapıcıları için öngörü ve tahminin çok kritik bir önemi olduğunu göz önüne aldığmızda, bu çalışmanın önemi ortaya çıkmaktadır. Ayrıca politika yapıcılarına tahminlerimizin güvenilir ve kuvvetli (robustness) olduğu gösterilerek bazı politika önerileri sunuldu. Öncelikle endüstri üretimine bakılarak ekoniminin gidişatı üzerinden donuk krediler hakkında öngörüde bulunulabilir. Çalışmada kullanılan modelin tahmin kabiliyetinin çok yüksek olduğu göz önünde bulundurularak donuk krediler düzenleyici kurumlar tarafından kontrol edilebilir.

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CONTENTS

FIGURES

TABLES

CHAPTER 1

INTRODUCTION

Recent global financial crisis which affected the whole world critically, said to be one of the biggest crisis in last century even considering the Great Depression. Many financial institutions go into bankruptcy or bailed out by governments in the developed countries. Therefore credit risk, especially mortgage credits in the example of recent crisis has gained more attention both by policy makers and academicians. In the case of Turkey, we experienced many financial crises in a very short period of time. One of the severest crisis in Turkey’s history is 2000-2001 financial crisis erupted from the banking system. Hence financial stability stands as one of the main areas to improve for the policy makers. After the painful experience of 2000-2001 financial crisis, Turkey achieved to implement considerable and significant regulatory policies with the help of the establishment of autonomous regulatory agencies. Moreover Turkish Central bank gained its autonomy in 2000s which enables price stability and monetary policy effectiveness. During this period, as a consequence of tight monetary and fiscal policy and comprehensive institutional reforms, the inflation declined significantly, and the financial system went through structural changes (Başçı, 2005).

In the aftermath of the current financial crisis Turkish financial market and banking sector was sound and performed well comparing with the developed and other developing countries. This stable condition of the Turkish financial market can be attributed to both the newly established regulatory agencies after the 2000-2001 crisis and the structure of the Turkish banking system. Commercial banks in Turkey, as the main players of the market, still use conventional banking products heavily and derivative products are not very much familiar to Turkish investors. This conventional structure of the Turkish banking system, protected the banks to be infected by the recent global financial crisis which mainly erupted based on derivative products. However, with the significant contraction in economic activity, the decrease in employment, resulting fall in credit demand, and the increased cost of credit funds from international funding sources, the Turkish banks have experienced decrease in credit volume since the last quarter of 2008. Besides, the sector's loan risk has begun to increase since the last quarter of 2008. The non-performing loans[1] (NPLs) of the sector have increased by 12.8% and reached TL 21.2 billion within the third quarter of 2009 compared to the previous quarter. The NPLs ratio has increased to 5.3 % in this quarter (BRSA, September 2009).

The definition of NPL may change from country to country but the general definition according to Basel II criteria, loans which are overdue more than 90 days and does not accrue interest are classified as NPL. In Turkey according to BDDK (Banking Regulation and Supervisory Agency) there are 5 categories of loan definitions depending on their overdue dates;

1) Loans of a Standard Nature and Other Receivables (Standart Nitelikli Krediler ve Diğer Alacaklar): Performing Loans without any due date problem

[1] Non-performing Loan will be referred as "NPL" throughout the text

2) Loans and Other Receivables Under Close Monitoring (*Yakın Izlemedeki Krediler ve Diğer Alacaklar*): Loans which are overdue more than 30 days but less than 90 days
3) Loans and Other Receivables with Limited Recovery (*Tahsil Imkânı Sınırlı Krediler ve Diğer Alacaklar*): loans which are overdue more than 90 days but less than 180 days
4) Loans and Other Receivables with Limited Recovery(*Tahsili Süpheli Krediler ve Diğer Alacaklar*): Loans overdue more than 180 days but less than 1 year
5) Loans and Other Receivables Having the Nature of Loss (*Zarar Niteliğindeki Krediler ve Diğer Alacaklar*): Loans overdue more than 1 year

According to this classification of loans the loans under category 3, 4 and 5 are defined as NPL (*Donuk Alacaklar*) consistent with the Basel II definition.

NPL level has increased steadily from the December 2002 to August 2009, except the decrease in the first quarter of 2004. This period is favorable in terms of both global and domestic economic conditions. The syndication and securitization credits became less costly for Turkish banks, as Turkey stabilize its economy with low interest rate and inflation, and initiation of EU negotiations (Aysan et al., 2009). In this study we used NPL ratio as an endogenous variable since it is more accurate indicator for the performance of Turkish banking sector. Figure 1 shows that the ratio of NPL declined steadily until the August 2008 (when the effect of global financial crisis hit the world). This decline is not because the level of NPLs decreased during the period, but because the sectors' total loans (credit) level increased. Before 2001 crisis, the banks were reluctant to give credits, and public sector borrowing requirement was very high (Aysan et al., 2009). After the crisis, the sectors' total assets, total deposits and total loans steadily increased. So, the Turkish banks performed considerably well by expanding credit with almost the same level of NPLs. However, with the banks' reluctance to give credits, the credits began to decline, and the level of NPLs began to increase with the first sign of the global financial crisis in August 2008. Therefore, the NPL ratio has rapidly increased since then, and has reached to 5.3 % in September 2009. Even a level of %5 NPL ratio is not such a severe level considering the pre-2000 period. After December 2009, banks realizing that Turkish economy is not affected as developed countries, continue giving credits and as a result NPL ratio declined again.

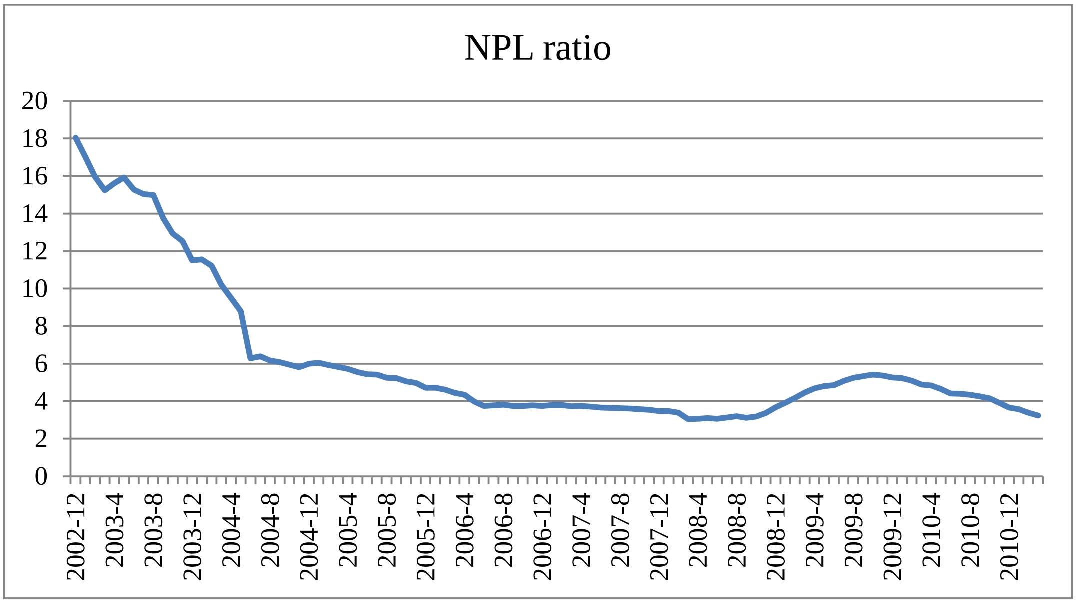

Figure 1: Evolution of NPL ratio in Turkey

Stress-testing can be defined as the techniques used by policy makers (central banks, regulators, banks) to assess the vulnerability of the financial system (macro stress-testing) or individual banks to extreme events.

This study is the first study about Macro-stress testing for Turkey in the literature, in the best of my knowledge. Yet there are a few studies about the determinants of Non-Performing Loans (NPL) in Turkey. Karabulut and Bilgin (2007) examine the effect of unlimited deposit insurance system on NPLs, and analyze other potential determinants of NPLs using data from 1987:1 to 2002:1. They conclude that the unlimited deposit insurance system positively affects the NPLs by damaging efficiency of allocation of deposits. Masood and Stewart (2009) analyze the determinants of NPLs and banking costs during the 1999-2001 crisis period. They use survey level data employing ordered choice models. They find that unnecessary government intervention, connected lending, poor credit risk assessment, and a weak capital base of Turkish commercial banks were the main determinants of NPLs for the relevant period.

Surprisingly there appears to be no publicly available or published study analyzing the NPLs for Turkey after 2000-2001 crisis period. Thus this study is first attempt not only for macro stress-testing for Turkish financial sector but also first study revealing the basic determinants of NPLs. We employed a 7-lag VAR model focusing on the NPL ratio as a proxy for credit risk to make inference about the financial stability of the Turkish economy. Our model include 7 endogenous variables which are NPL (NPL ratio), CAPACITY (capacity usage), SPREAD (difference between interest on yearly cash credit and 1-year TRL government bond), INDUSTRY (industry production), INDEBT (total credits/total assets of the sector), CLI1 (composite leading indicator) and EXPAN (credit expansion).

The outline of the study is planned as follows: In the next part I summarize the existing literature on macro stress-testing, in the following part I will describe the data and the methodology used in the study. After that, I will present the dynamic out of sample forecast results and impulse response analysis in a stress-testing framework. Before the conclusion part I will exhibit a scenario based macro stress-testing results and finally I will conclude.

Literature Review

Considering the recent global financial crisis, financial stability gained much more importance. A significant number of researches have been done in the literature about the financial stability issue. It is not a surprise that these studies concluded that financial stability is sensitive to macro-economic shocks. Demirgüç-Kunt and Detragiache (1998) analyze the determinants of banking crisis and concluded that banking crises are related with macro-economic environment. A similar study held by Hardy and Pazarbasioglu (1998) also have similar conclusions. Gambera (2000) used a VAR model to analyze the effect of macro variables on problematic loans such as Non-performing loans (NPL), and concluded that macro variables are significantly predict banks' loan quality. Kearns (2004) focused on Irish Institutions with a fixed affects panel data model concluding that macroeconomic variables such as GDP growth and unemployment have a significant effect on loan loss provisions increase.

A branch of this vast literature focuses on the macro stress-testing, which can be defined as a tool for assessing the stability of the financial system as a whole from a macro perspective. In a broader sense, stress-testing can be regarded as a "what if" exercise to analyze the possible consequences of an event or shock (Bunn et. al, 2005). The macro stress-tests are usually held by regulatory agencies and central banks of the countries.

IMF and World Bank has established a joint program in 1999, named as Financial Stability Assessment Program (FSAP) which is defined by IMF as; " a comprehensive and in-depth analysis of a country's financial sector". Since the FSAP was launched in 1999, after the Asian crisis, more than 130 countries have volunteered to participate in the program. Turkey was not voluntary to become a member of the program at the beginning. However it become a compulsory member, after the landmark decision by the IMF's Executive Board on September 21, 2010 converts the financial stability component of the voluntary Financial Sector Assessment Program (FSAP) into a mandatory part of the IMF's surveillance for the world's top 25 financial sectors (http://www.imf.org/external/pubs/ft/survey/so/2010/new092710A.htm).

Macro stress testing is a key quantitative analytical tool in FSAP and many countries held macro stress tests as a part of the program. There are different macro stress-testing methodologies which can be classified into three main categories (Maechler, 2008);

- Top-down vs. bottom-up approach: In the top-down approach the impact of stress test results are estimated using aggregated data where in the bottom-up approach the impact is estimated using data on individual portfolios.

- Balance sheet vs. Risk based method: In balance sheet approach the stress-test is evaluated on the basis of the balance sheet by using linear regression methods such as VAR, whereas in the risk based approach Value at Risk (VaR) methodology is used via employing monte-carlo analysis.
- Single shock vs. Scenario Analysis: Single shock analysis held by giving a shock only to a single variable, where as in the scenario analysis a hypothetical macro scenario shock is constructed, sometimes and a macro scenario contains multi-variable shock.

In most of the FSAP countries single factor sensitivity analysis is conducted. However, in recent years, FSAP analyses have evolved through multi-factor sensitivity analysis and macro scenario analysis[2]. There are different risk factors used in the literature such as; credit risk, market risk (FX risk etc.), liquidity risk, and contagion risk. There are number of studies which take credit risk into consideration. Pesola (2005) identifies macroeconomic indicators of credit risk for the Nordic countries, Belgium, Germany, Greece, Spain and the UK using an econometric model estimated on panel data from partly the early 1980s to 2002. Boss (2002) and Boss et al. (2004) use credit risk approach to analyze the Austrian banking system. Kalirai and Scheicher (2002) used a time series regression of aggregate loan loss provisions to conduct a stress test for Austrian banking system, with a focus on the impact of credit risk. Baboucek and Jancar (2005) used NPL ratio as an indicator of Czech banking sector's loan quality and analyzed the relationship between NPL ratio and macroeconomic variables by employing a VAR model. After performing

[2] For detailed view of application methodologies used by FSAP countries, see Čihák (2007), Appendix III.

impulse-response analysis and stress testing methodology they conclude that the macro variables used in the model can be appropriate early warning indicators.

Hoggarth et al. (2005) analyze the dynamics between banks' write-offs and key macroeconomic variables, by employing a Vector Auto Regression (VAR) model for UK banking system. Roy and Bhattacharya (2011) investigate the dynamic impact of changes in macroeconomic variables on default rate for Indian banking system using VAR model. Filosa(2007) conducts a stress-test for Italian banking system by the estimation of three alternative VAR models each using different indicators of banks' soundness: the ratio of non-performing loans (flow and stock data) and interest margins to outstanding loans. Also there are some papers such as Boss (2003) and Virolainen (2004) analyze the credit risk on a risk based method (VaR) using the framework developed by Wilson (1997).

There are also some survey-based and discussion-based studies on macro-stress testing application and methodologies. For example Sorge (2004) reviews the state-of-the-art macro stress testing experience and methodologies. Blaschke et al. (2001) and IMF and World Bank (2003) give examples of the analytical tools used across countries in the FSAP experience, while Drehmann et al. (2004) review some approaches and results used in UK for macro stress-testing as a part of the FSAP. Jones et al. (2004) intend to answer some of the basic questions that may arise as part of the process of stress testing and also provide an overview of the process itself, from identifying vulnerabilities, to constructing scenarios, to interpreting the results. Worrell (2004) suggests a strategy designed to make best use of the available quantitative techniques of financial sector assessment.

Cihak (2007) reveals a study on applied stress testing by pointing out the strengths and weaknesses of the stress testing methodology used in the literature. He presents an Excel-based exercise by institution specific data and also analyzes the other analytical tools for financial stability such as financial soundness indicators and early warning systems with surveying recent stress testing practices used by IMF and central banks.

Schmieder et al. (2011) introduces a next generation balance sheet stress testing framework extending on the basis of the work of Cihak (2007). They try to present a stress testing methodology via enriching the risk-sensitivity, transparency, flexibility with a more user-friendly framework.

Tracey (2006) employs an unrestricted VAR model to analyze the effects of Jamaica’s macroeconomic condition on banking sector’s loan quality via using Non-performing loans. He concludes that both monetary and structural influences play a critical role in the level of NPLs. He also performs macro stress-test simulating a worst-case scenario analysis and the results suggest that there is a little evidence of systemic threat for the Jamaican banking system.

An expertise qualification thesis of Turkish Central Bank (TCMB), Beşe (2007) presents the case of Turkey. However the study is mainly depends on Cihak (2007) and seems to be a translation of Cihak(2007). Beşe (2007) helds a simple IRF analysis.

In this study our methodology can be classified as a top down, balance-sheet approach with a focus on credit risk using NPL as a proxy for credit risk. We utilize both a single shock and scenario analysis on the basis of a vector auto regression (VAR) model.

Data and Methodology

Data

Monthly data series spanning the period 2002:12 – 2011:4 is used for the estimation of VAR model. We used monthly data instead of quarterly data, since quarterly data is less volatile and there would be a critical loss of information in quarterly data. The data starts from last month of 2002 because the previous Non-Performing Loan (NPL) data is not reliable enough. Moreover, the NPL ratio data taken from BDDK starts from December 2002. Since we use monthly data and GDP data is available quarterly, we use Industry production and Capacity usage as a proxy for the state of the real economy. In the literature many macro-economic indicators used for the determinants of NPL such as FX, terms of trade, budget balance, indebtness, credit growth, CPI (Consumer Price Index), unemployment rate, terms of trade etc. In our model, we used CLI (Composite Leading Indicators) to reduce the dimensionality, since CLI includes[3] basic marco-variables used in the literature. Using CLI is one of the main contributions in this study.

[3] For a detailed explanation of CLI of Turkey see: Atabak, Coşar, Şahinöz (2005)

Table 1: Brief Definition of Variables Used in the Model

Variable Name	Conceptual Definition	Operational Definition	Source of Data
NPL	Non-performing loan of sector / Total loan of sector	Logarithm of NPL ratio	BDDK
CAPACITY	Capacity Usage	First Difference of Logarithm of Deseasonalized (by Census X-12 Method) Capacity Usage	TCMB-TÜİK
SPREAD	yearly cash credit interest MINUS 1-year TL government bond	First Difference of Logarithm of Spread(which is used as a proxy for the expectations of banks)	AUTHORS
INDUSTRY	Industry Production	First Difference of Logarithm of Deseasonalized (by Census X-12 Method) Industry Production	TCMB-TÜİK
INDEBTNESS	Total Credit of Sector / Total Assets of Sector	First Difference of Logarithm of Indebtness	BDDK
CLI1_SA	Composite Leading Indicator - 1	First Difference of Logarithm of Deseasonalized (by Census X-12 Method) Composite Leading Indicator 1	TCMB
CLI2	Composite Leading Indicator - 1	First Difference of Logarithm of Composite Leading Indicator 1	TCMB
CLI3	Composite Leading Indicator - 1	First Difference of Logarithm of Composite Leading Indicator 1	TCMB
EXPAN	Credit Expansion	Logarithm of Credit Expansion	BDDK

We used both capacity usage and industry production since they capture different proxies in the economy with different lags although they seem to be very similar. There are two main reasons that we think they capture different proxies. Firstly their scope differ; secondly industry production includes quantity and values of both production and sales where as capacity usage simply shows the recent capacity used. Thus industry production shows the real state of the economy as a proxy for GDP.

INDUSTRY, CLI1 and CAPACITY are deseasonalized by using Census X-12 method. CLI2 is used as its level. Also CLI3 is used as it is, since it is defined as 6-month rate of change.

We include “interest” variable as a SPREAD; which is defined as the spread between the “yearly cash credit interest” charged by banks and “1-year TL government bond”, to capture the expectations of banks.

INDEBTNESS is defined as the ratio of the “total credit” of the sector to the “total assets” of the banking sector.

EXPAN is used for credit expansion, which is defined as the credit expansion from the previous period. This variable is included to capture the credit dynamics of the industry

We used all variables by taking their logs to adjust the scaling within them and also checked for stationarity, by performing Augmented Dickey-Fuller test[4]. All variables except NPL and INDEBTNESS are found to have unit root. Thus they are used by taking first-difference and after differencing they are found to be stationary. The descriptive statistics of variables can be found in Appendix A.1

When we analyze correlation between CLI’s there is not high correlation between their levels but when we take their first difference there is a strong correlation.[5] Also when we look at the CLI’s as we used in the data (deseasonalized

[4] The results of Dickey Fuller test can be found in Appendix A.1

[5] See Appendix A, Table A.2 for correlation results.

CLI1 and taking first difference of the other two), deseasonalized CLI1 do not highly correlated with the other two.

Table 2: Correlation of CLI's as used in the model

	CLI1_SA	CLI2	CLI3
CLI1_SA	1.000000	0.673536	0.568168
CLI2	0.673536	1.000000	0.917412
CLI3	0.568168	0.917412	1.000000

Methodology

VAR model made popular by Sims (1980) is an econometric model used to analyze the dynamic feedback relationship between multivariate time series data. In the VAR model all variables are used as endogenous variables and all endogenous variables has a linear equation based on its own lags and other variables' lags. Thus number of equations in a VAR model is equal to the number of endogenous variables. The structural form of our VAR model can be described as follows:

$$\begin{bmatrix} Y_{1t} \\ \vdots \\ Y_{7t} \end{bmatrix} = \begin{bmatrix} A_1 \\ \vdots \\ A_7 \end{bmatrix} \begin{bmatrix} Y_{1t-1} \\ \vdots \\ Y_{7t-1} \end{bmatrix} + \begin{bmatrix} u_1 \\ \vdots \\ u_7 \end{bmatrix}$$

where Y_{1t} , … ,Y_{7t} represents the endogenous variables of NPL, CAPACITY, INDUSTRY, SPREAD, INDEBT, CLI1 and EXPAN. u_t are the error terms of the linear equations and A_1, … , A_7 are 1×7 coefficient matrix of the endogenous variables

In a more compact form:

$$Y_t = B + A(L)\ Y_{t-1} + u$$

where Y_t is 7×1 vector of endogenous variables; $A(L)$ is an 7×7 matrix of the lag operator polynomials containing lags of the endogenous variables and u is the 7×1 vector of white noise error terms, which have the property, $u \sim \mathrm{N}(0, \Omega)$.

In this study, we used a standard VAR model with 7 lags. Since we are restricted with 101 monthly data constraint, we decided to use 7 lags although AIC recommends[6] higher lag orders. In fact lag order should not exceed %10 of the number of lags. Moreover, when we use 8 lags the stability conditions are not satisfied for the VAR model.[7] Also considering economic intuition 7 month period seems reasonable for the NPL write off for the banks

We conduct Granger-Causality test to see whether all endogenous variables are granger causes NPL in NPL equation. The table below shows that all endogenous variables except INDUSTRY have significantly (within the %90 confidence interval) explains NPL equation.[8] However since ALL is significantly explaining NPL equation.

[6] See Appendix A Table A.3 for lag length results

[7] See Appendix B Tables B.2 and B.3 for eigenvalues of 8 lag model

[8] For the granger causality results of other equations please see Appendix B

Table 3:Granger Causality Wald Tests

Equation	Excluded	chi2	df	Prob>chi2
NPL	CAPACITY	27.246	7	0.0000
NPL	SPREAD	35.595	7	0.0000
NPL	INDUSTRY	7.7609	7	0.3540
NPL	INDEBT	30.01	7	0.0000
NPL	CLI1	23.163	7	0.0020
NPL	EXPAN	12.178	7	0.0950
NPL	ALL	266.94	42	0.0000

We also conduct stability and normality tests to check the robustness of our model. As it can be seen from the Graph 1 below, VAR satisfies stability condition since all eigenvalues lie inside the unit circle (all eigenvalues are less than 1) [9]

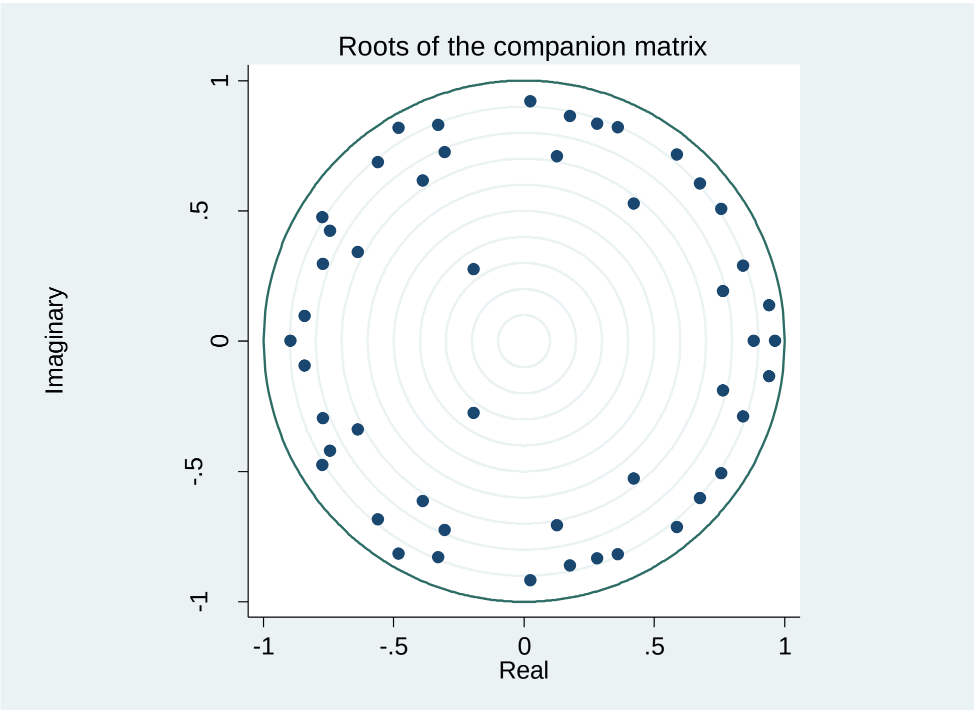

Figure 2: Eigenvalue stability of VAR with 7 lags

[9] See Appendix B, Tables B.2 and B.3 for stability and normality results

Estimation Results

We used CLI1 (composite leading indicator 1) for VAR model estimation, since it is defined by the trend restored CLI where as CLI 3 is defined as the 6-month rate of change[10]. Moreover CLI1 leads a better forecasting power than CLI2. But we also estimated a model including all the three CLI's, because forecasting power increases significantly when we include all CLI's in the model.[11]

From probability column (P>z column) of the VAR estimation results with 7 lags; it seems that only second lag of industry production (INDUSTRY) and credit expansion (EXPAN) is significant. But here we must consider the structure of the VAR models and keep in mind that interpreting directly from the VAR coefficient estimate results and p-values may not be appropriate and we should use Impulse Response analysis for the interpretation. As Tracey (2011) points out; the typical overparamatization problem of an unrestricted basic VAR model doubled with some significant collinearity among the regressors, may lead a reduction in the reliability of some of the t-statistics. Hence, although inference directly from coefficient estimates of the VAR may be misleading and difficult to make, impulse response analyses and forecasting will give reasonable and useful results to make interpretation.

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[10] For a detailed explanation of CLI of Turkey see: Atabak, Coşar, Şahinöz (2005)

[11] See Appendix C

Table 4: VAR estimation Results

Sample: 2003-9 - 2011-3	No. Of obs=	91
Log likelihood = 2351.555	AIC=	-43.99
FPE = 4.81e-28	HQIC=	-40.094
Det(Sigma_ml) = 8.46e-32	SBIC=	-34.333

Equation	Parms	RMSE	R-sq	chi2	P>chi2
NPL	50	0.01331	0.9966	26528.5	0
CAPACITY	50	0.00803	0.7175	231.15	0
SPREAD	50	0.01234	0.8711	614.804	0
INDUSTRY	50	0.01686	0.7628	292.649	0
INDEBT	50	0.0055	0.9985	60323.5	0
CLI1	50	0.004	0.8788	659.719	0
EXPAN	50	0.01709	0.7504	273.595	0

NPL Equation

	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
NPL						
L1.	0.951571	0.116464	8.17	0	0.7233063	1.179835
L2.	-0.43477	0.157723	-2.76	0.006	-0.7439012	-0.12564
L3.	0.660279	0.160697	4.11	0	0.3453181	0.97524
L4.	-0.0984	0.177795	-0.55	0.58	-0.4468767	0.250067
L5.	-0.01241	0.168825	-0.07	0.941	-0.3433037	0.318478
L6.	0.085848	0.15733	0.55	0.585	-0.2225131	0.394208
L7.	-0.25223	0.106978	-2.36	0.018	-0.4619063	-0.04256
CAPACITY						
L1.	0.380397	0.180602	2.11	0.035	0.0264242	0.73437
L2.	0.127123	0.217425	0.58	0.559	-0.299022	0.553268
L3.	0.684101	0.221899	3.08	0.002	0.2491867	1.119016
L4.	0.140364	0.23045	0.61	0.542	-0.3113088	0.592037
L5.	0.389323	0.208786	1.86	0.062	-0.0198896	0.798535
L6.	0.131411	0.187419	0.7	0.483	-0.2359245	0.498746
L7.	-0.26587	0.13662	-1.95	0.052	-0.5336442	0.001896
SPREAD						
L1.	0.420089	0.106862	3.93	0	0.2106443	0.629534
L2.	-0.13501	0.130129	-1.04	0.3	-0.3900529	0.120042

L3.	0.160688	0.128035	1.26	0.209	-0.0902554	0.411632
L4.	0.06931	0.124507	0.56	0.578	-0.1747204	0.31334
L5.	-0.38475	0.109595	-3.51	0	-0.5995511	-0.16995
L6.	-0.01315	0.095477	-0.14	0.89	-0.2002868	0.173978
L7.	-4.6E-05	0.078437	0	1	-0.1537803	0.153688

INDUSTRY

L1.	-0.14725	0.090918	-1.62	0.105	-0.3254426	0.030947
L2.	-0.31028	0.149573	-2.07	0.038	-0.6034353	-0.01712
L3.	-0.25061	0.183195	-1.37	0.171	-0.609668	0.108442
L4.	-0.0313	0.195712	-0.16	0.873	-0.4148894	0.352286
L5.	0.024809	0.195215	0.13	0.899	-0.357805	0.407424
L6.	-0.03627	0.163701	-0.22	0.825	-0.3571209	0.284575
L7.	0.006493	0.093432	0.07	0.945	-0.1766307	0.189616

INDEBT

L1.	-0.84616	0.255244	-3.32	0.001	-1.346426	-0.34589
L2.	-0.1199	0.347942	-0.34	0.73	-0.8018586	0.56205
L3.	1.162391	0.336002	3.46	0.001	0.5038396	1.820943
L4.	-0.32226	0.362401	-0.89	0.374	-1.032556	0.388031
L5.	-0.11328	0.365158	-0.31	0.756	-0.8289757	0.602416
L6.	0.296641	0.358318	0.83	0.408	-0.40565	0.998931
L7.	-0.18784	0.268082	-0.7	0.484	-0.7132701	0.337593

CLI1

L1.	-0.54672	0.355664	-1.54	0.124	-1.24381	0.150367
L2.	0.292921	0.41089	0.71	0.476	-0.5124089	1.098252
L3.	0.195868	0.433368	0.45	0.651	-0.6535183	1.045254
L4.	-1.45167	0.43424	-3.34	0.001	-2.302765	-0.60058
L5.	1.185088	0.392499	3.02	0.003	0.4158037	1.954372
L6.	-1.04311	0.402915	-2.59	0.01	-1.832812	-0.25341
L7.	0.377103	0.32854	1.15	0.251	-0.2668227	1.021029

EXPAN

L1.	0.000403	0.091644	0	0.996	-0.1792173	0.180022
L2.	-0.27302	0.111419	-2.45	0.014	-0.4914009	-0.05465
L3.	0.064218	0.106207	0.6	0.545	-0.1439446	0.27238
L4.	0.091486	0.104628	0.87	0.382	-0.1135806	0.296553
L5.	-0.06723	0.097694	-0.69	0.491	-0.258711	0.124242
L6.	-0.10148	0.089378	-1.14	0.256	-0.2766617	0.073693
L7.	0.098829	0.071702	1.38	0.168	-0.0417044	0.239362

_CONSTANT	0.282265	0.082866	3.41	0.001	0.1198512	0.444678

CHAPTER 2

FORECASTING

Out of Sample Dynamic Forecast

The dynamic out of sample estimation method is as follows; firstly some of the data at the end is reserved for benchmark for the estimation error. The model starts estimating from the period before the reserved period of benchmark. By this methodology we have the opportunity to analyze how much the forecasted values deviate from the actual values and can calculate a measure representing the forecast accuracy of the model. The dynamism of this model is that; the forecasted values are calculated step by step as such that the next periods value is calculated using the last forecasted value. There are different measures for forecast accuracy but SPE's (Square percentage error) seems more informative since they show how much the forecasted value deviate from the actual as a percentage. Thus we calculated RMSPE (Root Mean Square Percentage Error) for our dynamic out of sample forecast. The RMSPE (root of MSPE) is calculated as below, where Y_t represents the actual value of the data and F_t represents the forecasted value coming from the estimated VAR model;

$$E_t = Y_t - F_t \tag{1}$$

E_t is the error term, representing the deviation from the actual value,

MSPE (Mean Square Percentage Error) is calculated as below;

$$MSPE = \frac{\sum\left(\frac{E_t}{Y_t}\right)^2}{N}$$

$$RMSPE = \sqrt{MSPE}$$

Diebold-Mariano test, developed by Diebold and Mariano (1995) aims to test the equality of expected forecast accuracy as a null hypothesis. The formal procedure of the test is as follows:

Let Y_t denote the actual series to be forecasted and let there are two competing forecasts F_{t+h}^1 and F_{t+h}^2 that are h step ahead dynamic out of sample forecasts. For example, in our context one could be computed from an AR (7) model and the other could be computed from a 7-lag VAR model. The forecast errors E_{t+h}^1 and E_{t+h}^1 which are calculated as in equation (1) above. Then the accuracy of each forecast is measured by a loss function such as MSE, MAPE etc.

$$L(Y_t , F_{t+h}^i) \ = \ L\left(E_{t+h}^i\right), i = 1,2 \tag{2}$$

To determine whether one model has a better forecast accuracy than another we will test the null hypothesis

$$H_0: E[L(E_{t+h}^1)] \ = \ E[L(E_{t+h}^2)]$$

Against the alternative

$$H_1: E[L(E_{t+h}^1)] \ \neq \ E[L(E_{t+h}^2)]$$

The Diebold-Mariano test is based on the loss differential

$$dt = L(E_{t+h}^1) - \ L(E_{t+h}^2)$$

The null hypothesis is then

$$H_0: E[dt] = 0$$

The Diebold-Mariano test statistic is

$$S = \frac{\bar{d}}{(\widehat{avar}(\bar{d}))^{1/2}} = \frac{\bar{d}}{(\widehat{LRV}_{\bar{d}}\ /T)^{1/2}}$$

where

$$\bar{d} = \frac{1}{T}\sum_{t=t_0}^{T} d_t$$

$$\widehat{LRV}_{\bar{d}} = \gamma_0 + 2\sum\nolimits_{t=t_0}^{T}\gamma_j\ ,\ \ \gamma_{j=cov(d_t, d_{t-j})}$$

and $\widehat{LRV}_{\bar{d}}$ is a consistent estimate of the asymptotic (long-run) variance of $\sqrt{T}\bar{d}$ The long-run variance is used in the statistic because the sample of loss differentials $\{d_t\}$ are serially correlated for h> 1. Diebold and Mariano (1995) show that under the null of equal predictive accuracy $S \sim N(0,1)$ asymptotically, so we reject the null of equal predictive accuracy at the 5% level if $S > 1.96$

For forecasting NPL ratio, we used an AR(7 lags)[12] model as a benchmark model to see whether our model (comparing with the benchmark AR(7)) improves forecast capacity significantly or not. From Diebold-Mariano test both of CLI1[13] and All CLI (Table 5 below) models statistically significantly is a better forecast than NPL-AR model.

[12] We used 7 lags to have the same basis with our model. Indeed AIC criteria suggests AR(4) model

[13] See Appendix C, Table C.1 for Diebold-Mariano results of CLI1 vs. NPL AR(7)

Table 5: Diebold-Mariano for NPL AR(7) vs. All CLI models for after period 70

Diebold-Mariano forecast comparison test for actual : lognpl	
Competing forecasts: "NPL_AR_lognpl" versus "All_CLI_70" Criterion: MAPE over 33 observations Maxlag = 9 chosen by Schwert criterion Kernel : uniform	
Series	MAPE
NPL_AR_lognpl	0.1350
All_CLI_70	0.0433
Difference	0.0917
By this criterion, "All_CLI_70" is the better forecast	
H0: Forecast accuracy is equal.	
S(1) = 3.065 p-value = 0.0022	

For Dynamic out of Sample Forecast, we checked whether forecast accuracy of All CLI model improves significantly on the CLI1 model. The Diebold-Mariano test result in the Table 6 below shows that the VAR model with All CLIs is a statistically better model than CLI1, meaning that the explenatory power of the VAR model increases if we inlcude all CLI's in the model. Thus we prefer to use the model containing all CLIs as the base model for forecasting purposes. The forecast accuracy improvement of All CLI model can be also seen from the Figure 3 below; the solid line which represents the model of All CLIs is capturing the cyclical behavior of NPL accurately.[14]

[14] See Appendix C figure C.2 for different specification dynamic out of sample forecasts estimated after 75th period(after February 2009)

Table 6: Diebold-Mariano for CLI1 vs. All CLI models for after period 70

Diebold-Mariano forecast comparison test for actual : lognpl	
Competing forecasts: CLI1_70_lognpl versus All_70_7lag Criterion: MAPE over 33 observations Maxlag = 9 chosen by Schwert criterion Kernel : uniform	
Series	MAPE
CLI1_70_lognpl	0.07694
All_70_7lag	0.04331
Difference	0.03363
By this criterion, All_70_7lag is the better forecast	
H0: Forecast accuracy is equal.	
S(1) = 2.903 p-value = 0.0037	

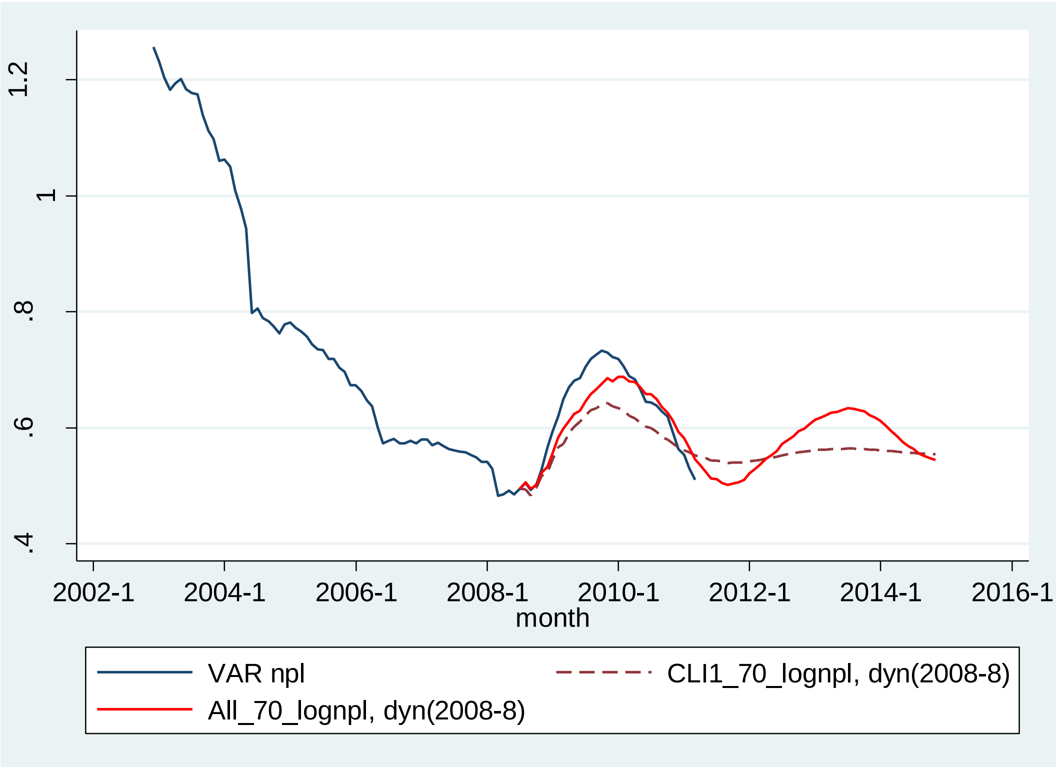


Figure 3: Log(NPL) graph for Out of Dynamic Forecast after September 2008

Figure 3 above suggests that NPL ratio will drop at until September 2011 and after that it starts to increase till July 2013 and drops again after the end of 2013. This cyclical forecast result, which shows the forecast capacity of our model, is one of outstanding contributions of this study, since we can capture the cyclical behavior with a linear model (VAR model).

Moreover a VAR model with only 3 of the CLI's and logNPL as a dependent variable, also have a significant improvement on NPL-AR model. When we compare this “onlyCLI” model with AR model by using Diebold-Mariona test; we found that onlyCLI significantly has a better forecast capacity (Table 7). This result strengthens our choice of using CLI as an endogenous variable in the VAR model, since even with only CLI's we can improve forecasting accuracy compared with NPL-AR(7) model. In fact, onlyCLI model also captures the cyclical behaviour of the actual data when we perform a dynamic out of sample forecast from February 2009 (Figure 4).

Table 7: Diebold-Mariano for NPL AR(7) vs. ONLY CLIs models for after seventieth period

Diebold-Mariano forecast comparison test for actual : lognpl	
Competing forecasts: "NPL_AR_lognpl" versus "onlyCLIs_70" Criterion: MAPE over 33 observations Maxlag = 9 chosen by Schwert criterion Kernel : uniform	
Series	MAPE
NPL_AR_lognpl	0.1350
onlyCLIs_70	0.1104
Difference	0.0246
By this criterion, "onlyCLIs_70" is the better forecast	
H0: Forecast accuracy is equal.	
S(1) = 2.528 p-value = 0.0115	

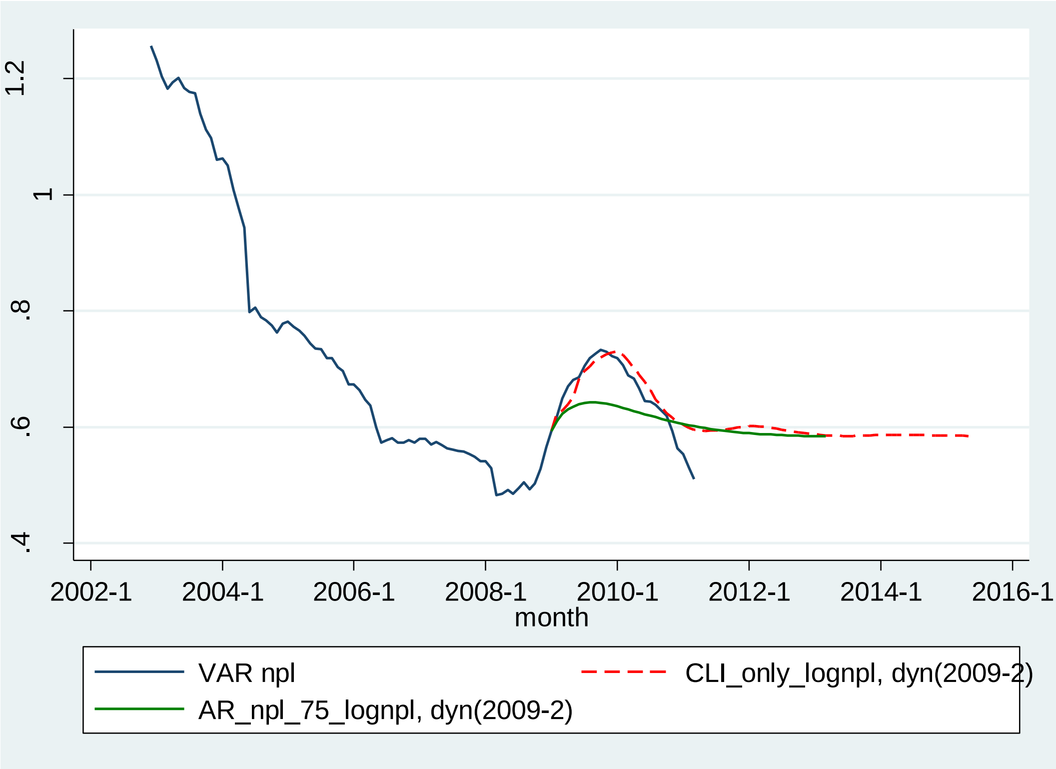


Figure 4: onlyCLI model vs. NPL AR model

Robustness of the Forecast

We checked the robustness of our model via forecasting NPL ratio staticly. Static forecasting is calculated by performing a series of one-step ahead forecasts of the dependent variable via using actual values; whereas in the dynamic forecast, forecasted values are calculated dynamically using previously forecasted values. In the static forecast parameters are reestimated after each period so that static forecast is more robust in parameter estimation. On the other hand, dynamic forecast is not robust for parameter estimation as parameters are not reestimated in every step. Therefore we checked the robustness of our dynamic out of sample forecast results by comparing it with static forecast results. As it can be seen from Figure 5 below, the dynamic out of sample results estimated after seventy fifth period (after February

2009) are quite accurate even we compared it with static forecast estimated after seventy fifth period. Thus we conclude that, the model constructed in this study performs quite well for forecasting NPL ratio and policy makers can use it with mind at peace.

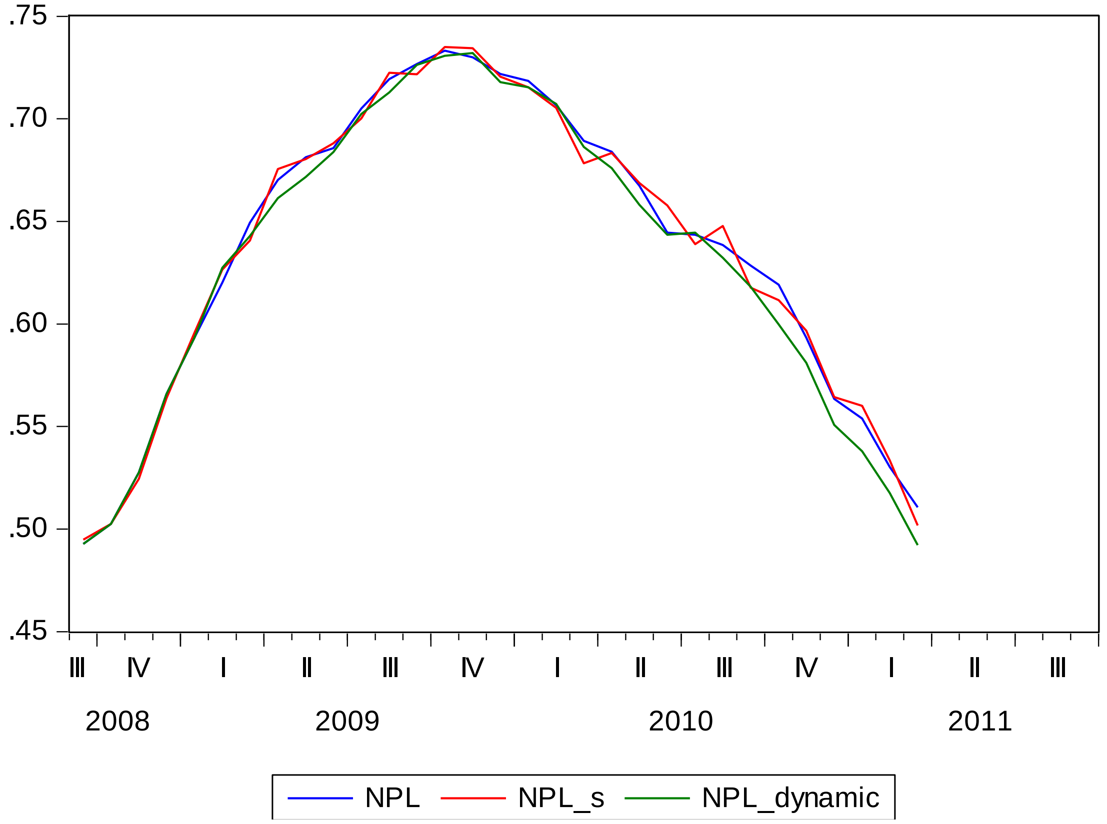


Figure 5:Static vs.Dynamic out of sample forecast resutls after September 2008

CHAPTER 3

MACRO STRESS TESTING AND IMPULSE RESPONSE ANALYSIS

Impulse Response Analysis

Consider a VAR model with p lags

$$Y_t = A_1 Y_{t-1} + \cdots + A_p Y_{t-p} + u_t$$

where Y_t is a K×1 vector of endogenous variables and u_t is a K×1 vector of white noise error terms. We can rewrite the VAR model in moving-average form

$$Y_t = \alpha + \sum_{i=0}^{\infty} \beta_i \, u_{t-i} \tag{3}$$

where α is the K×1 time invariant mean of Y_t, and

$$\beta_i = \begin{cases} I_K & if\ i = 0 \\ \sum_{j=1}^{i} \beta_{i-j} A_j & if\ i = 1,2,\ldots \end{cases}$$

The β_i are the simple IRFs. The j, k element of β_i gives the effect of a 1–time unit increase in the k^{th} element of u_t on the j^{th} element of Y_t after i periods, holding everything else constant. Unfortunately, these effects have no causal interpretation, which would require us to be able to answer the question, “How does an innovation to variable k, holding everything else constant, affect variable j after i periods?” Because u_t are contemporaneously correlated, we cannot assume that everything else is held constant. Contemporaneous correlation among u_t implies that a shock to one variable is likely to be accompanied by shocks to some of the other variables, so it does not make sense to shock one variable and hold everything else constant. For this reason, (3) cannot provide a causal interpretation.

This shortcoming may be overcome by rewriting (3) in terms of mutually uncorrelated innovations. Suppose that we had a matrix P, such that $\sum = PP'$, then $P^{-1}\sum P'^{-1} = I_K$ and,

$$E\{P^{-1}u_t(P^{-1}u_t)'\} = P^{-1}E\{(u_t u_t')P'^{-1}\} = P^{-1}\sum P'^{-1} = I_K$$

We can thus use P^{-1} to orthogonalize the u_t and rewrite (3) as;

$$Y_t = \alpha + \sum_{i=0}^{\infty} \beta_i P P^{-1} u_{t-i}$$

$$= \alpha + \sum_{i=0}^{\infty} \Theta_i \, P^{-1} u_{t-i}$$

$$= \alpha + \sum_{i=0}^{\infty} \Theta_i \, h_{t-i}$$

where $\Theta_i = \beta_i P$ and $h_t = P^{-1}u_t$. If we had such P, then h_k would be mutually orthogonal,and no information would be lost in the holding-everything-else-constant assumption, implying that Θ_i would have the causal interpretation that we seek. For choosing such P, Sims (1980) popularized the method of choosing P to be theCholesky decomposition of $\widehat{\sum}$ The IRFs based on this choice of P are known as the orthogonalized IRFs. Choosing P to be the Cholesky decomposition of $\widehat{\sum}$ is equivalent to imposing a recursive structure for the corresponding dynamic structural equation model.

Priori Expectations

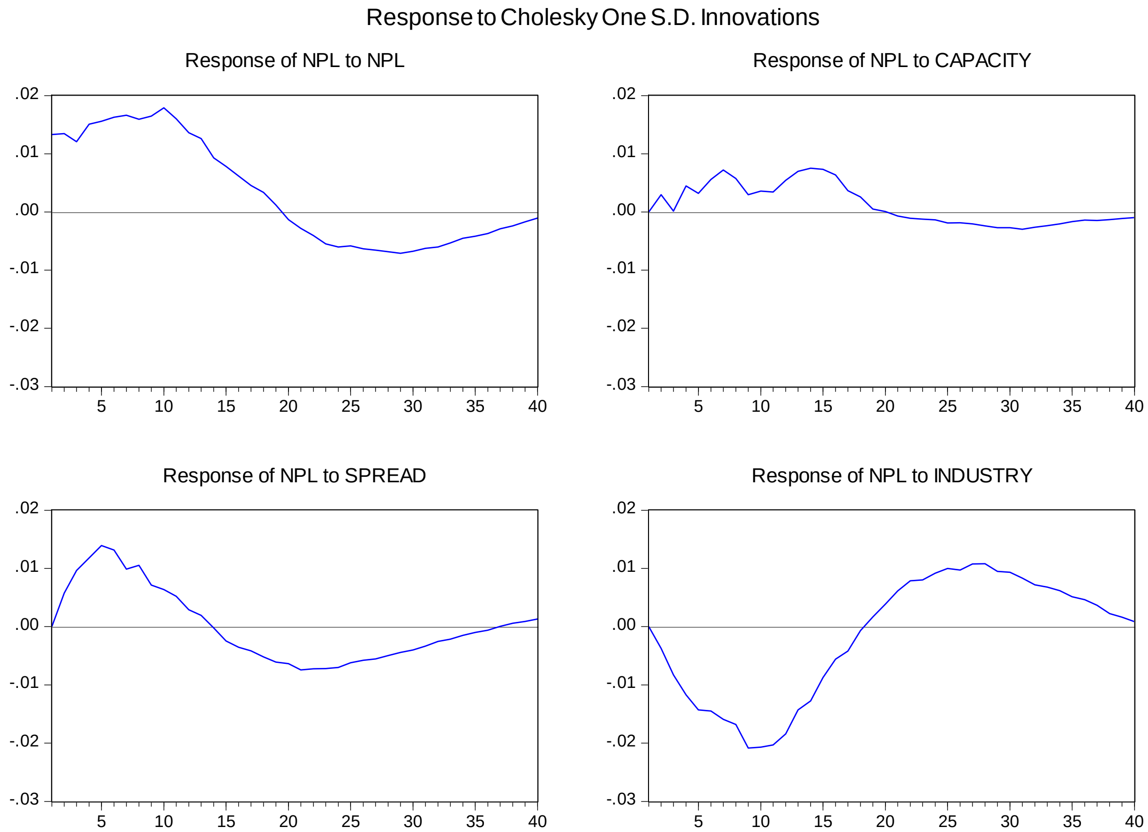
NPL ratio is defined as the ratio of non-performing loans on total loans. So when the real economy grows and gets better, we expect NPL ratio to decline. Considering this negative relation between NPL and the real economy, we have a priori expectation that the response of NPL ratio will be declining to a positive shock on CAPACITY, INDUSTRY PRODUCTION and CLI's. Moreover; since INDEBTNESS is defined as the ratio of total credits /total assets of the banking industry, we expect NPL ratio to decrease at first and increase accordingly as INDEBTNESS increases. The reasoning is as follows: Considering NPL ratio is defined as NPL/Total Credits, an increase in INDEBTNESS means an increase in total credits which comes as a denominator in NPL ratio. Thus at first NPL ratio will decline but after some point NPL itself will tend to increase resulting increase in NPL ratio.

Since SPREAD, which is defined as the difference between yearly cash credit and 1-year government bond, can be interpreted as a proxy of the expectation of Banks about the future state of the economy, we may have a priori expectation that response of NPL to a positive shock on SPREAD is increasing.

Single Variable Stress-Testing: Orthogonalized Impulse Response Results

Simulations of the responses should be performed for a sufficiently long period in order to detect regularity in them. Normally, 30 or more periods are used in the literature, we used 40 periods in this study. Since the covariance matrix of the VAR residuals is not diagonal, the residuals need to be orthogonalised. A common procedure used in the literature is to apply a Cholesky decomposition, which is equivalent to adopting a particular ordering of the variables and allocating any correlation between the residuals of any two elements to the variable that is ordered first. It is obvious that these impulse response functions may be sensitive to the ordering of the variables. Thus in our model we also adopt Cholesky decomposition in which variables are ordered considering variance decomposition on NPL equation.[15] In the ordering method, former variables have more more variance in the NPL equation and latter have less. By this criteria we ordered variables as: NPL, CAPACITY, SPREAD, INDUSTRY, INDEBT, CLI1, EXPAN. The VAR model is also estimated using a different ordering of the variables, but no significant change in the results is detected.

[15] See Appendix D for variance decomposition of variables



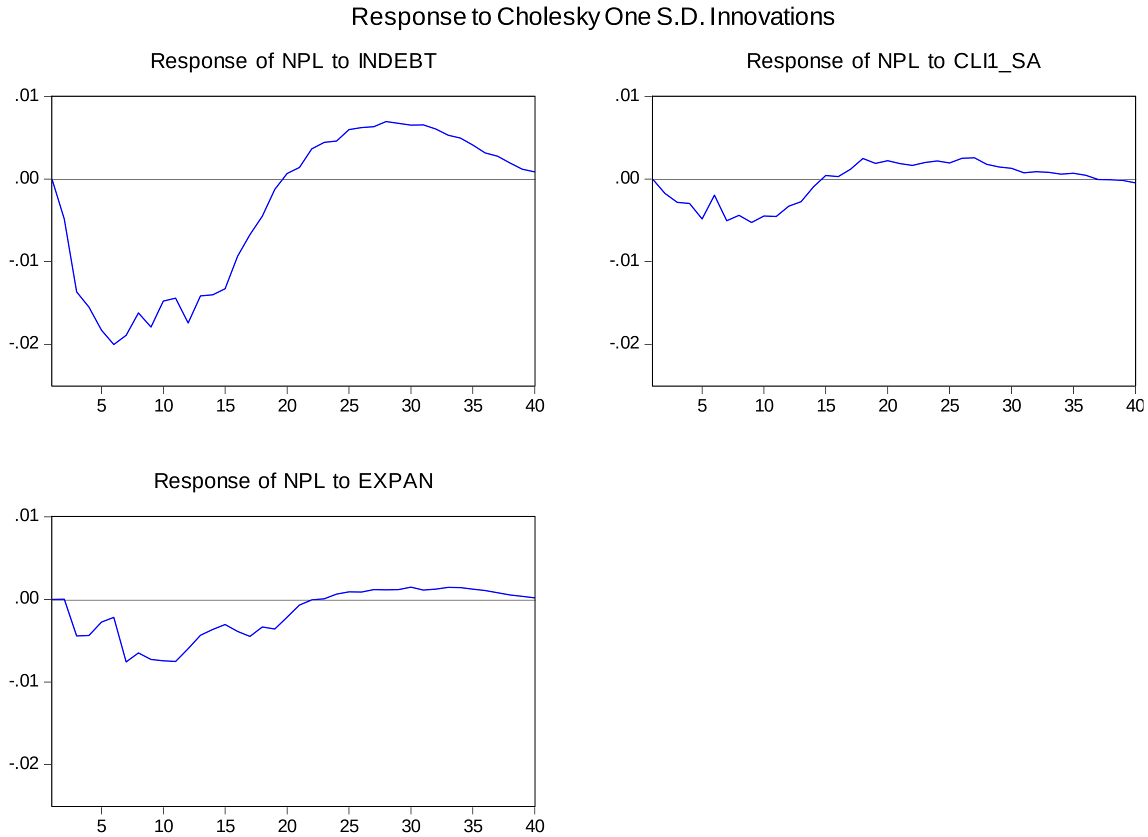


Figure 6: Response of NPL on cholesky one standard deviation shocks

All the variables in the model are in logarithms so we can easily interpret the results in terms of percentage changes.

Response of NPL to shocks on NPL, SPREAD, INDUSTRY, CLI1, INDEBT are consistent with priori expectations; where shocks on CAPACITY is just the opposite of the priori expectations.

Specifically a positive Cholesky one Standard Deviation (S.D.) shock on NPL itself increases NPL until 20 period (month) ahead, which is consistent with our priori expectations. After twentieth period NPL ratio tends to decline due to two reasons; firstly since NPL ratio is increased before twentieth period banks tend to behave more strictly while giving credits which may increase the quality of the new issued credits also some Non-Performing credits excluded from balance sheets since they are written off as loss.

Similarly, a positive Cholesky one S.D. shock on Capacity Usage increased NPL ratio. Here the relation between capacity and NPL ratio seems just the opposite of the priori expectations. This result can be interpreted such that; a positive capacity shock meaning that the increase in capacity usage will lead to an increase in the borrowing behavior of the firms (which are the biggest credit users in Turkey). With the confidence on the economic environment, firms may tempt to borrow heavily, which may result in an increase in the NPL ratio.

A positive shock on SPREAD results in an increase in NPL, which is consistent with our priori expectations. SPREAD which is defined as the difference between the interest rate charged for cash credit by banks and 1-year government TL bond is used as a proxy for the expectations of the banks. Considering this definition an increase in the spread means a wider gap between the interest rate charged by banks and government bond which means banks are expecting a slowdown in the economy. Also the increase in spread means that banks are charging more for the credits which may result in adverse selection problem and a decrease in the loan quality. These two phenomena lead an increase in NPL ratio. After thirteenth period (month) NPL ratio starts to decline, this can be interpreted as follows: During 13 period the more risky loans written as NPL and NPL ratio increased, but after period 13 less risky (more qualified) loans have left so that NPL ratio tends to decline.

A positive shock on INDUSTRY means that economy gets better so as a priori expectation we will comment that NPL ratio will decline. The IRF results are consistent with the priori expectation, which is one of the main strengths of our model; because INDUSTRY is used as a proxy for GDP growth and borrowers paying ability should increase as the economy gets better. The NPL ratio declines until 18th month since borrowers tend to pay their loans easily with a stimulus in the economy; but after 18th month NPL ratio starts to increase again, because this time new borrowers who borrowed in a stimulus period in the economy may not pay their loans when the economy slows down.

The response of NPL to a positive shock on INDEBTNESS is an immediate decrease in NPL which is consistent with priori expectations. An increase in INDEBTNESS refers to an increase in total credits, which is in the denominator of the NPL ratio definition. So, immediate decrease in NPL ratio is logical. After 20 months, NPL itself increases where as “total credits” stays same resulting with an increase in NPL ratio.

Interpretation of response of NPL to a positive shock on CLI1 is the same as the INDUSTRY. The only difference is CLI1 has a less significant effect on NPL.

EXPAN which is credit expansion also has the same interpretation with INDEBTNESS, since a positive shock to both of them means an increase in total credits.

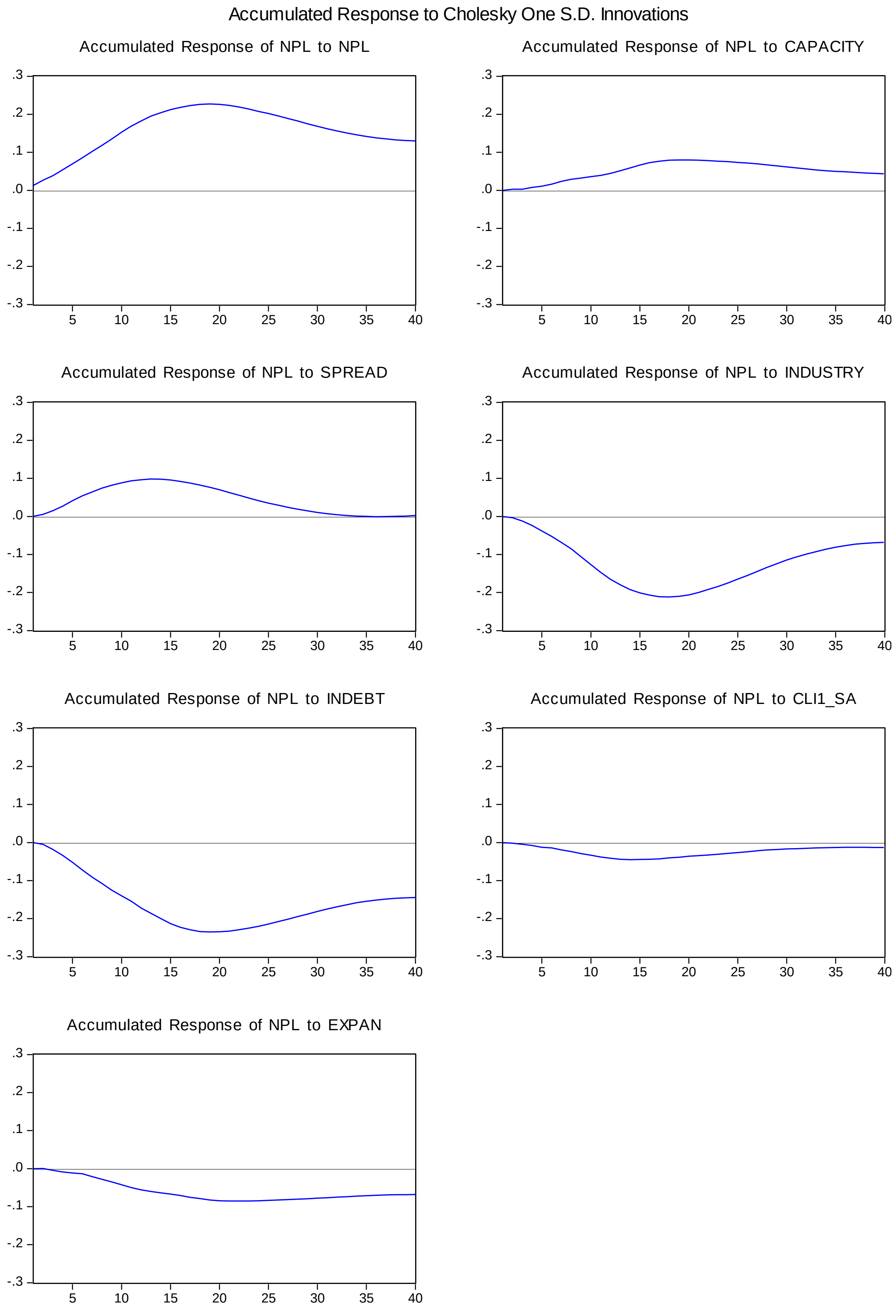


Figure 7: Accumulated Response of NPL on Cholesky One S.D. Shocks

For the representation of impulse response analysis accumulated IRF graphs are also used (table above) since it is a descriptive tool for cumulated affects of the shocks on NPL ratio. Moreover as we used the log of the variables in the model, we can easily interpret the change in the level of NPL ratio due to shocks.

Specifically a Cholesky one standard deviation Innovation on NPL(lognpl) itself, which can interpreted as a 1% increase, results with an increase in lognpl by 0.226 till nineteenth period, meaning that NPL ratio is increased by 22.6% cumulatively of its previous level.

Similarly, a positive Cholesky one S.D shock on Capacity Usage increased NPL ratio 8% cumulatively up to twentieth period.

Cumulative response of NPL ratio to one S.D shock (1% increase) in SPREAD is 10% increase up to the thirteenth month.

NPL ratio declines as a response to a positive shock on Industry Production. Up to the nineteenth month ahead, NPL ratio decreases by 21.1% cumulatively.

This result has the same interpretation with the explanation given about CAPACITY. When people expect a better environment they increase their borrowing behavior. In the aftermath when economy slows down, NPL ratio increases. In the long-run NPL ratio increases by 5.6% due to the shock, on the contrary to priori expectations. This phenomenon can be explained such that; people increase their expectations much further than the real increase in the economy. These interpretation of CAPACITY and CLI shocks can be a good example of discrepancy of expectations on the efficient market hypothesis.

When we look both the short and long-term pattern of accumulated response of NPL to shock on other endogenous variables; the long term accumulated effect of CLI1, Indebtness and Credit Expansion seems insignificant. On the other hand Capacity Usage (CAPACITY) has the most significant effect in the long-run.

Macro Stress-testing with Scenario Analysis

There are two ways of creating macro scenarios. One of them is reevaluating the past crisis and the other is creating a hypothetical scenario. We choose to simulate a historical Macro scenario which recreates the current financial crisis. In the last month of 2008 (December 2008) INDUSTRY dropped by %14.3, CAPACITY dropped by %9.6, CLI1 dropped by %8 and finally SPREAD increased by %9. These crisis time shocks used in our scenario analysis and the impulse response results are obtained (Graph .. below).

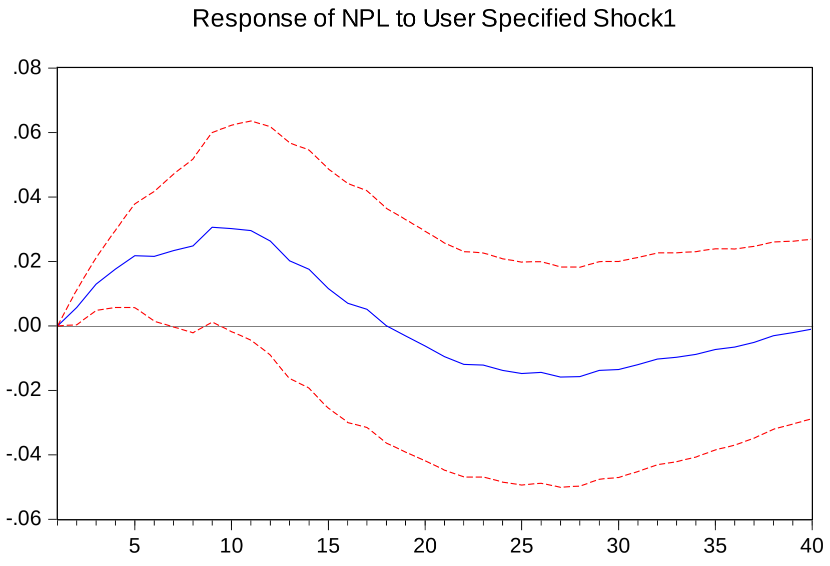


Figure 8: Response of NPL on macro scenario shock

To analyze the cumulative effect of this scenario shock we used Accumulated Response as shown in the Figure 9 below. The response of NPL ratio to macro scenario shock is %3 increase after 15 periods (months). This result shows us that NPL ratio is quite stable on a one time shock reproduced based on crisis period. Therefore financial fragility of the system is quite stable, considering the current state of the economy.

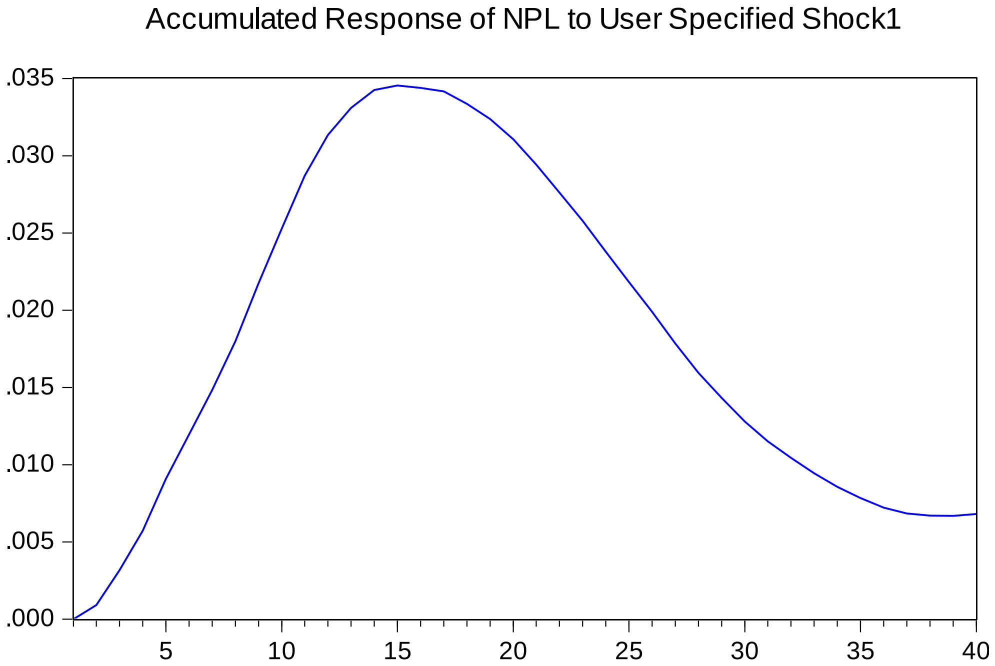


Figure 9: Accumulated Response of NPL on macro scenario shock

CHAPTER 4

POLICY IMPLICATIONS AND CONCLUSION

Policy Implications and Recommendations

Recent global financial crisis showed that financial stability is a very crucial international issue and no country has the confidentiality to state that it is not concerning about financial stability. Moreover, financial stability of a country not only concerns itself but also the entire world due to high interdependence and reciprocity of financial markets. That's why international and national authorities, regulators seek for an early warning system. This study focusing on the credit risk, which is one of the main elements of the financial stability, tries to improve a model that will give an early warning for the authorities and central banks via using Non-performing loan ratio as a proxy for the credit risk. Considering that, for Turkey main actors of the financial market is the conventional commercial banks and their main instrument is loans, one can realize the importance of the NPLs for Turkish economy. Therefore, by utilizing the methodology developed in this study, NPL ratio can be used as an alternative proxy for financial status of the Turkish economy. The VAR model developed in this study captures the cyclical behavior of the NPL ratio very accurately even when we perform out of dynamic forecast for the last 30 observations (30% of the total observation) of the data.[16] It is obvious that nobody can argue that only one proxy will be enough for evaluating the financial stability of an economy. Thus forecasted NPL ratio values can be used as an alternative proxy

[16] See Figure 3 and 5 in the "Out of Dynamic Forecast" section.

with financial soundness indicators. Figure 10 below shows in sample forecast after the last observation of the data. The model forecasts NPL ratio to decrease at 2.7% until September 2011 and consequently to increase at 4.4% until August 2013 and a slight decrease again after that (Figure 10 below). This cyclical behavior can be attributed to the aging effect of the loans.

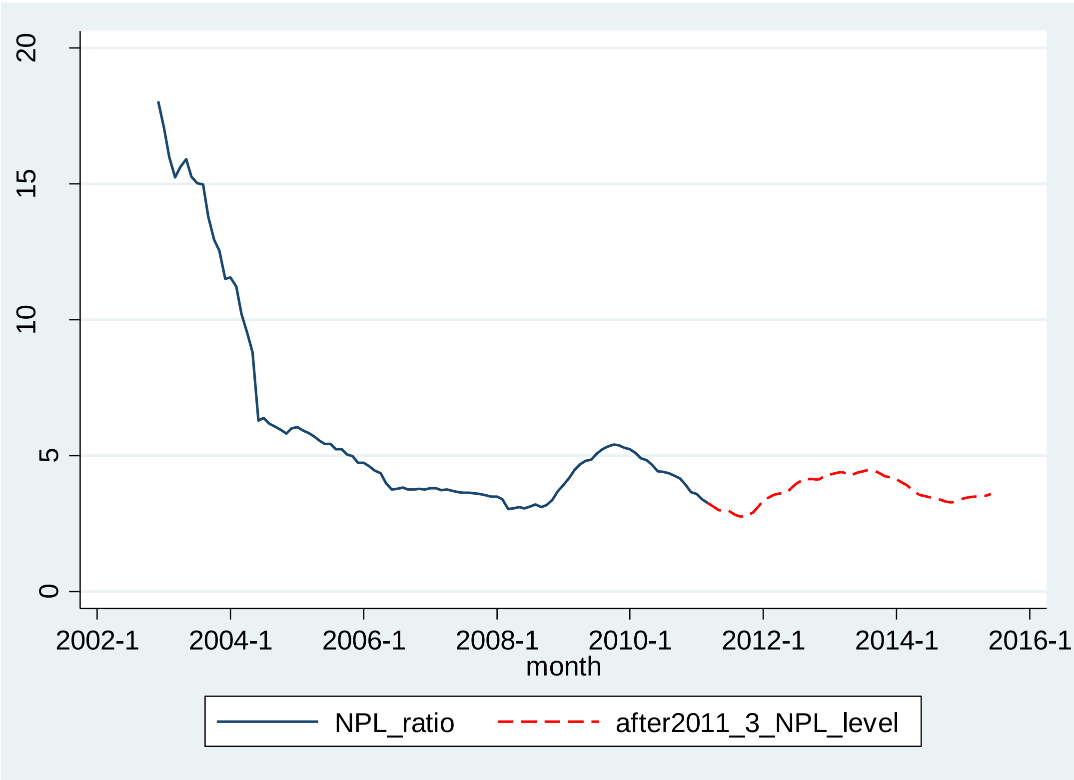


Figure 10 : NPL ratio forecast based on the VAR model

Policy implications that can be inferred from this study can be as follows;

- Industry production which is used as proxy for the state of the real economy is one of the most significant explanatory variables for NPL ratio. Thus policy makers should bear in mind this relation for financial stability. The stimulus in the economy firstly decreases NPL ratio but after a 1.5 year the NPL ratio starts to increase but not as high as critical levels.

- Capacity Usage which can be also interpreted as a proxy for the real economy also has a significant effect but just the opposite of the priori expectations. Thus policy makers should concern that firms (main borrowers in Turkey) borrowing heavily with expectations far optimistic than the real stimulus in the economy and, may go into a bankruptcy when there is even a slight slowdown in the economy. This asymmetry of expectations of the firms and the stimulus in the real economy should be concerned by regulators, policy makers and banks.
- Spread which is used as a proxy for the expectations of the banks seems to reflect the market direction accurately. However one should be careful about making inference by looking at the IRF results of Spread, because a shock on Spread results with an increase on NPL not only due to banks' appropriate expectations about the future state of the economy but also due to adverse selection problem, aging effect and old borrowers deterioration in their paying abilities.
- Using CLIs in the VAR model improves forecasting capacity significantly. Thus Central Bank should revise the study on constructing CLI series and bear this issue in mind.
- The forecast accuracy of model we used in study performs very well. The forecast almost exactly captures the real actual data when we perform a dynamic out of sample forecast after seventy fifth period. Bearing in mind that we have 100 observations and reserving 25% of the observation for

dynamic forecast, it is very promising that our model has very high forecast accuracy (see Figure 11 below). Thus policy maker can use our model for forecasting NPL ratio with a mind at peace.

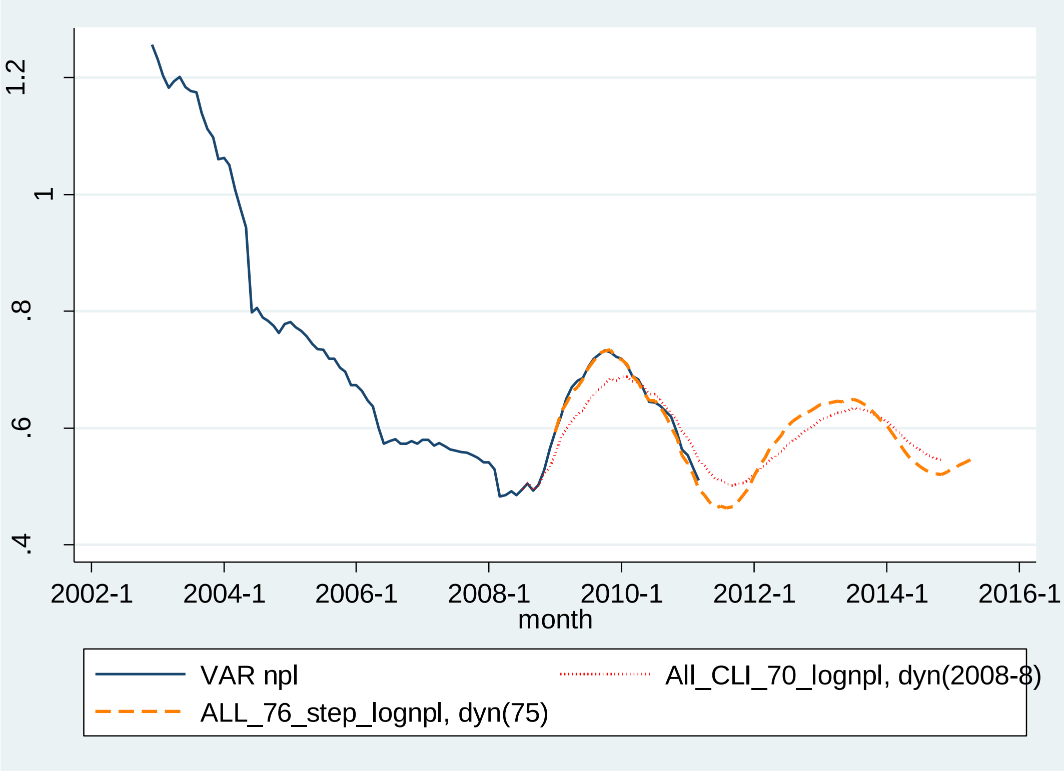


Figure 11: Forecast results of both after70 and after75 models

Conclusion

There is a vast literature on financial stability issue after the onset of the recent global financial crises. Stress-testing, as an analytical tool for assessing the fragility of the financial sector is one of the key issues in financial stability literature. The basic idea behind stress-testing is finding a risk proxy for financial stability and performing impulse response and sensitivity analysis on this proxy. There are different risk measures used in the literature such as credit risk, market risk (FX risk etc.), liquidity risk, and contagion risk. In this study we choose to analyze credit risk and use Non-performing loan (NPL) ratio as a proxy for the credit risk. The reason we focus on the credit risk is the financial structure of the Turkish economy. The main players in the market are conventional banks whose main operations are loans. Thus we think that NPL ratio will be a good proxy for assessing banks fragility and consequently financial sector stability.

Also there two types of methodology to apply stress testing; one is using bank level data and performing a Value at Risk (VaR) methodology, the other is using macro level data and applying times series methodologies such as VAR and VECM. This study can be classified into second methodology as a macro stress-testing, since we used macro level data employing VAR methodology.

We estimated a 7-lag VAR model with 7 endogenous variables which are NPL (NPL ratio), CAPACITY, SPREAD, INDUSTRY, INDEBT, CLI1 and EXPAN to perform dynamic out of sample forecast and impulse response analysis. The model used as a benchmark for dynamic out of sample forecast is the model includes all 3 CLIs, since all CLI model improves forecast accuracy significantly.[17] Our model captures a cyclical behavior accurately even we have used a linear model (VAR). This result is one of the main strengths and contributions in the literature of this study, since forecasting is a very crucial tool for both policy makers and market players.

After the experience of 2000-2001 Turkish financial crisis and establishment of new autonomous regulatory body Turkish financial sector become more stable and

[17] See "dynamic out of sample forecast" part of this study

less volatile. However one must be aware of that Turkish financial sector mainly uses conventional products and derivative products are not common. In fact, many Turkish investor are nor familiar with derivative products. Thus regulators must consider this issue and try to avoid a fragile financial system. Indeed the derivative product exchange market (VOB) in Turkey implemented a step by step approach to familiarize Turkish investors with derivative products. For example; option trading is not directly allowed but firstly only call option is allowed for regular investors.

This study as a first attempt for macro-stress testing applied on Turkish economy opens a window for further studies. We used NPL ratio as cumulative for all type of credits, but if micro level data such as the detailed NPL ratio for consumer credits, corporate credits etc. were available, one would have deducted more focused and accurate policy implications from macro-stress testing. Moreover we have only 100 periods (month) of data available due to unreliability of the data before 2000's. Thus this study can be extended by improving the data which would reveal more accurate and reliable results for policy implications. Another extension on this study may be linking this model with different satellite models such as models used by central banks for forecasting different basic macroeconomic variables.

APPENDICES

APPENDIX A: SUMMARY STATISTICS AND CORRELATION BETWEEN VARIABLES

Table A.1: Descriptive statistics

	NPL	CAPACITY	INDUSTRY	SPREAD	ONCU1	ONCU2	ONCU3	EXPAN	INDEBT
Mean	0.723	0.000	0.002	0.048	0.002	0.067	-0.030	0.026	1.601449
Median	0.672	0.000	0.003	0.054	0.002	0.140	-0.380	0.025	1.648645
Maximum	1.256	0.031	0.071	0.112	0.022	5.380	14.230	0.107	1.73228
Minimum	0.483	-0.031	-0.100	-0.128	-0.028	-8.670	-12.740	-0.034	1.34272
Std. Dev.	0.211	0.010	0.023	0.039	0.008	1.946	3.847	0.024	0.119059
Skewness	1.203	-0.160	-0.757	-2.243	-0.834	-1.165	0.608	0.492	-0.8846
Kurtosis	3.354	4.434	7.937	9.677	6.308	8.578	6.431	3.737	2.42757
Jarque-Bera	24.624	8.811	109.997	272.313	56.636	152.272	55.194	6.230	14.40724
Probability	0.000	0.012	0.000	0.000	0.000	0.000	0.000	0.044	0.000744
Sum	72.296	0.000	0.235	4.893	0.171	6.740	-3.020	2.564	160.1449
SumSq.Dev.	4.388	0.010	0.053	0.150	0.006	374.940	1464.863	0.058	1.403329
Observations	100	98	99	101	99	100	100	99	100

Table A.2: Correlation between variables as they are used in the model

Correl	NPL	CAPACITY	INDUSTRY	SPREAD	ONCU1	ONCU2	ONCU3	EXPAN	INDEBT
NPL	1	0.099535	0.050391	-0.19177	0.1711	0.189	0.099	0.107644	-0.929
CAPACITY	0.099535	1	0.036365	0.04926	0.287	0.1352	0.0018	0.190683	-0.074
INDUSTRY	0.050391	0.036365	1	0.12027	0.2983	0.1672	0.1266	0.104518	-0.028
SPREAD	-0.191773	0.049264	0.120272	1	0.3122	0.3151	0.2969	-0.16747	0.1618
ONCU1	0.17113	0.287049	0.298277	0.31225	1	0.6754	0.5694	0.020205	-0.084
ONCU2	0.189024	0.135187	0.167161	0.31507	0.6754	1	0.9174	-0.15296	-0.111
ONCU3	0.098995	0.001812	0.12655	0.29687	0.5694	0.9174	1	-0.26307	-0.046
EXPAN	0.107644	0.190683	0.104518	-0.16747	0.0202	-0.153	-0.2631	1	-0.205
INDEBT	-0.929141	-0.07439	-0.027579	0.16177	-0.0837	-0.1107	-0.0464	-0.20496	1

Table A.3: Lag length criteria

VAR Lag Order Selection Criteria
Endogenous variables: NPL CAPACITY SPREAD INDUSTRY INDEBT CLI1 EXPAN
Exogenous variables: C
Date: 07/20/11 Time: 09:13
Sample: 2002M11 2011M06
Included observations: 88

Lag	LogL	LR	FPE	AIC	SC	HQ
0	1457.190	NA	1.15e-23	-32.95887	-32.76181	-32.87948
1	1954.213	903.6774	4.35e-28	-43.14120	-41.56471*	-42.50607
2	2042.146	145.8895	1.83e-28	-44.02605	-41.07014	-42.83519
3	2090.285	72.20747	1.97e-28	-44.00647	-39.67113	-42.25987
4	2131.939	55.85458	2.58e-28	-43.83952	-38.12475	-41.53718
5	2175.961	52.02597	3.44e-28	-43.72638	-36.63219	-40.86831
6	2217.234	42.21166	5.45e-28	-43.55078	-35.07716	-40.13697
7	2305.428	76.16716	3.45e-28	-44.44154	-34.58850	-40.47200
8	2378.321	51.35635	3.87e-28	-44.98456	-33.75209	-40.45928
9	2446.812	37.35898	6.81e-28	-45.42755	-32.81566	-40.34654
10	2655.705	80.70847*	9.05e-29*	-49.06147*	-35.07015	-43.42472*

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

Table A.4: Eigen values of 8-lag model

Roots of Characteristic Polynomial
Endogenous variables: NPL CAPACITY SPREAD INDUSTRY INDEBT CLI1 ONCU2 ONCU3 EXPAN
Exogenous variables: C
Lag specification: 1 8
Date: 07/20/11 Time: 09:20

Root	Modulus
0.494328 - 0.876608i	1.006381
0.494328 + 0.876608i	1.006381
0.875387 - 0.488999i	1.002708
0.875387 + 0.488999i	1.002708
0.978761 + 0.167984i	0.993072
0.978761 - 0.167984i	0.993072
0.928552 + 0.341903i	0.989498
0.928552 - 0.341903i	0.989498
0.719324 + 0.662861i	0.978167
0.719324 - 0.662861i	0.978167
0.025360 - 0.976233i	0.976563
0.025360 + 0.976233i	0.976563
0.353809 - 0.902750i	0.969607
0.353809 + 0.902750i	0.969607
-0.500978 + 0.823785i	0.964158
-0.500978 - 0.823785i	0.964158
-0.820724 - 0.501619i	0.961878
-0.820724 + 0.501619i	0.961878

-0.540056 + 0.795185i	0.961239
-0.540056 - 0.795185i	0.961239
0.961230	0.961230
0.240444 - 0.928554i	0.959180
0.240444 + 0.928554i	0.959180
-0.624381 - 0.726781i	0.958155
-0.624381 + 0.726781i	0.958155
-0.887269 + 0.331996i	0.947347
-0.887269 - 0.331996i	0.947347
-0.409580 + 0.854180i	0.947300
-0.409580 - 0.854180i	0.947300
-0.251137 + 0.911387i	0.945355
-0.251137 - 0.911387i	0.945355
0.568377 + 0.754713i	0.944799
0.568377 - 0.754713i	0.944799
0.674472 + 0.656825i	0.941452
0.674472 - 0.656825i	0.941452
0.141945 + 0.929239i	0.940018
0.141945 - 0.929239i	0.940018
-0.760316 + 0.550710i	0.938809
-0.760316 - 0.550710i	0.938809
0.880261 + 0.309975i	0.933244
0.880261 - 0.309975i	0.933244
0.928905 + 0.052795i	0.930404
0.928905 - 0.052795i	0.930404
0.791339 - 0.486109i	0.928719
0.791339 + 0.486109i	0.928719
-0.926556 + 0.053258i	0.928085
-0.926556 - 0.053258i	0.928085
-0.061181 + 0.922212i	0.924239
-0.061181 - 0.922212i	0.924239
-0.904478 - 0.091066i	0.909051
-0.904478 + 0.091066i	0.909051
-0.823653 - 0.382595i	0.908176
-0.823653 + 0.382595i	0.908176
0.494180 - 0.752071i	0.899903
0.494180 + 0.752071i	0.899903
-0.167692 + 0.883902i	0.899668
-0.167692 - 0.883902i	0.899668
-0.870842 + 0.185879i	0.890459
-0.870842 - 0.185879i	0.890459
0.711407 - 0.530660i	0.887525
0.711407 + 0.530660i	0.887525
-0.455889 + 0.736400i	0.866095
-0.455889 - 0.736400i	0.866095
0.145849 - 0.784961i	0.798396
0.145849 + 0.784961i	0.798396
-0.637204 + 0.371735i	0.737710
-0.637204 - 0.371735i	0.737710
0.501573 + 0.266461i	0.567958
0.501573 - 0.266461i	0.567958
0.204591 + 0.527231i	0.565535
0.204591 - 0.527231i	0.565535
-0.391212	0.391212

Warning: At least one root outside the unit circle.
VAR does not satisfy the stability condition.

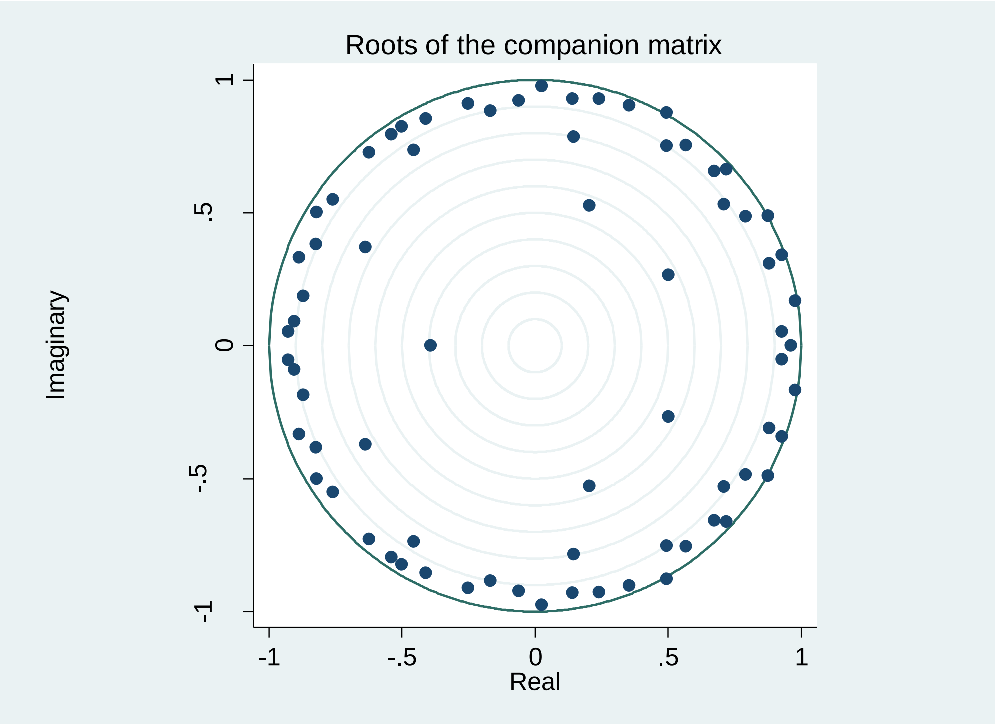


Figure A.1:Non-stable VAR model of 8 lags.

Table A.5: Correlation between levels of CLI's

correlation	CLI_1	CLI_2	CLI_3
CLI_1	1		
CLI_2	0.4989	1	
CLI_3	0.3871	0.6365	1

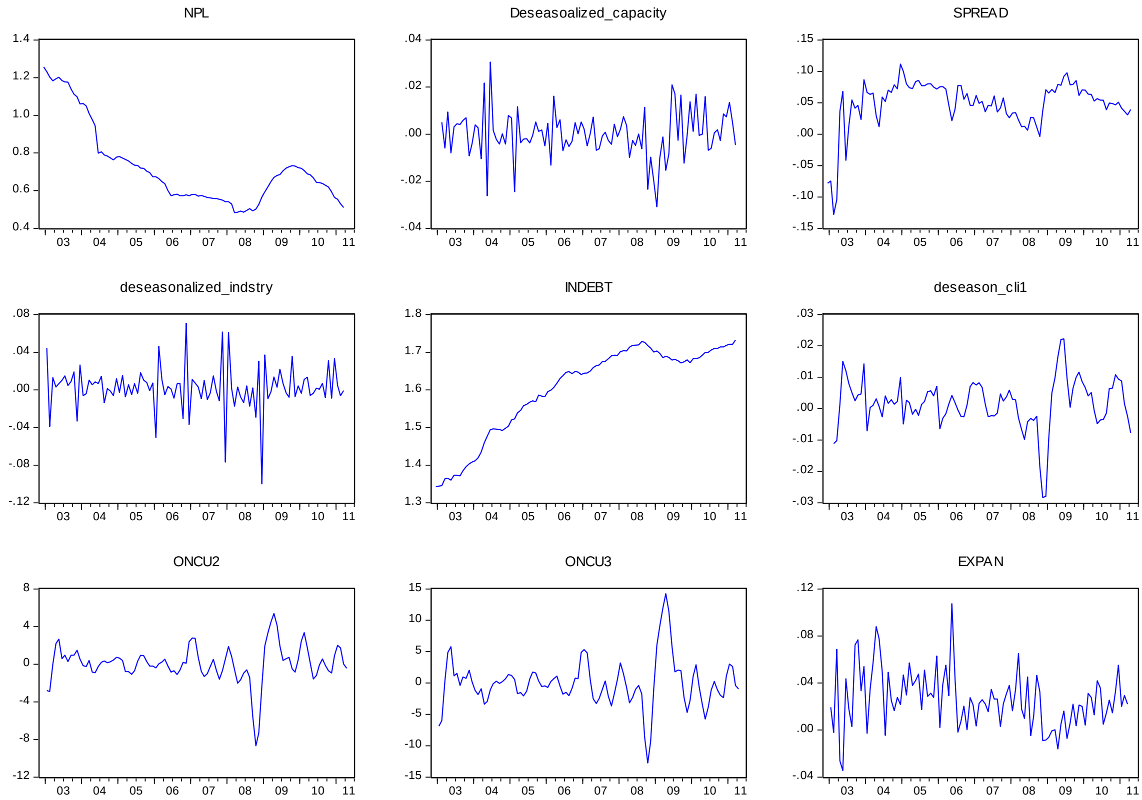


Figure A.2: Time Series of the levels of Endogenous Variables.

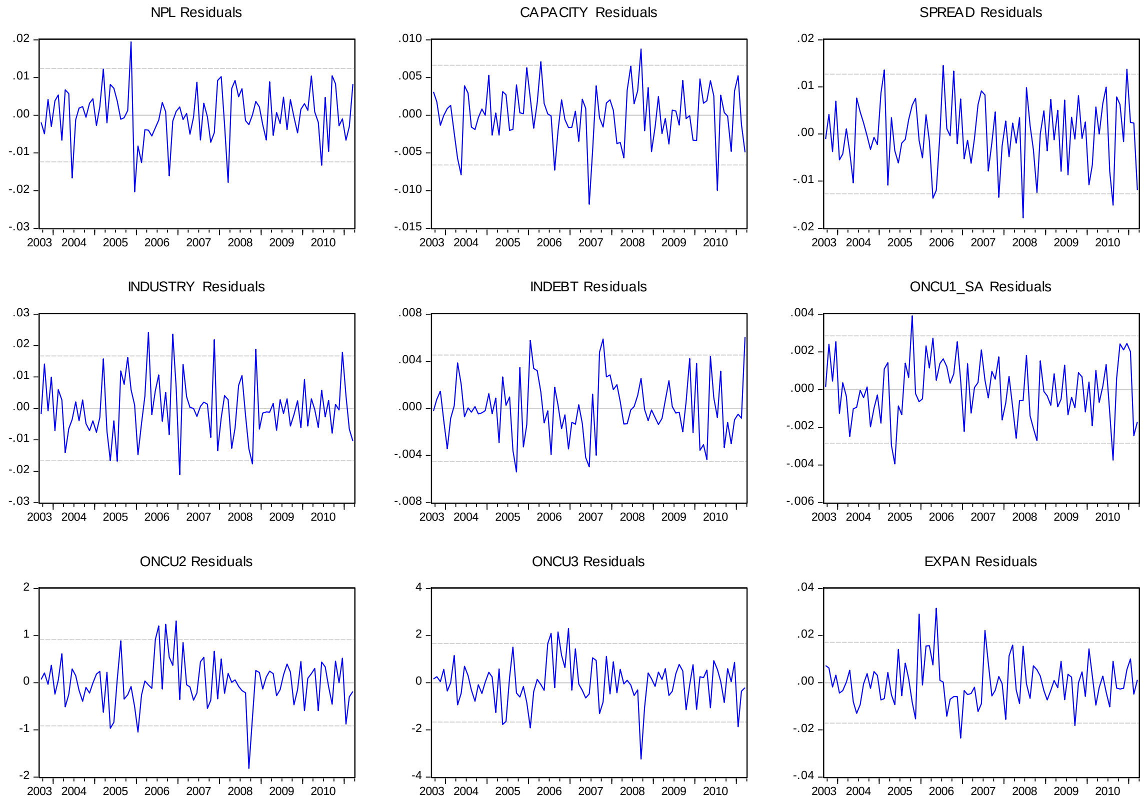


Figure A.3: Time Series of the levels of Endogenous Variables as used in the Model

APPENDIX B: STABILITY AND NORMALITY TEST RESULTS

Table B.1:Granger Causality Wald Tests

Equation	Excluded	chi2	df	Prob>chi2
d_logcapacity_sa	lognpl	18.987	7	0.008
d_logcapacity_sa	spread_adj	7.1257	7	0.416
d_logcapacity_sa	d_logindustry_s~n	16.754	7	0.019
d_logcapacity_sa	logindebt	5.9158	7	0.55
d_logcapacity_sa	d_logcli_season	43.741	7	0
d_logcapacity_sa	credit_expansion	6.3024	7	0.505
d_logcapacity_sa	ALL	199.28	42	0
spread_adj	lognpl	12.206	7	0.094
spread_adj	d_logcapacity_sa	14.997	7	0.036
spread_adj	d_logindustry_s~n	17.337	7	0.015
spread_adj	logindebt	54.302	7	0
spread_adj	d_logcli_season	13.137	7	0.069
spread_adj	credit_expansion	39.002	7	0
spread_adj	ALL	211.64	42	0
d_logindustry_s~n	lognpl	11.96	7	0.102
d_logindustry_s~n	d_logcapacity_sa	4.2042	7	0.756
d_logindustry_s~n	spread_adj	18.832	7	0.009
d_logindustry_s~n	logindebt	23.592	7	0.001
d_logindustry_s~n	d_logcli_season	35.53	7	0
d_logindustry_s~n	credit_expansion	12.049	7	0.099
d_logindustry_s~n	ALL	140.24	42	0
logindebt	lognpl	8.9384	7	0.257
logindebt	d_logcapacity_sa	21.705	7	0.003
logindebt	spread_adj	13.718	7	0.056
logindebt	d_logindustry_s~n	15.43	7	0.031
logindebt	d_logcli_season	28.768	7	0
logindebt	credit_expansion	22.879	7	0.002
logindebt	ALL	113.49	42	0
d_logcli_season	lognpl	37.335	7	0
d_logcli_season	d_logcapacity_sa	36.187	7	0
d_logcli_season	spread_adj	37.73	7	0
d_logcli_season	d_logindustry_s~n	25.368	7	0.001
d_logcli_season	logindebt	16.753	7	0.019
d_logcli_season	credit_expansion	49.177	7	0
d_logcli_season	ALL	229.98	42	0
credit_expansion	lognpl	7.1672	7	0.412
credit_expansion	d_logcapacity_sa	8.9779	7	0.254
credit_expansion	spread_adj	19.002	7	0.008

credit_expansion	d_logindustry_s~n	17.672	7	0.014
credit_expansion	logindebt	44.832	7	0
credit_expansion	d_logcli_season	21.585	7	0.003
credit_expansion	ALL	200.9	42	0

Eigenvalue stability condition

Eigenvalue	Modulus
.4886369 + .8672987*i*	.995476
.4886369 - .8672987*i*	.995476
.8573318 + .4880116*i*	.986495
.8573318 - .4880116*i*	.986495
.9276135 + .332612*i*	.985443
.9276135 - .332612*i*	.985443
.9714305 + .1518894*i*	.983233
.9714305 - .1518894*i*	.983233
-.5091255 + .8169142*i*	.962579
-.5091255 - .8169142*i*	.962579
.9601103	.96011
.7146328 + .6280771*i*	.95141
.7146328 - .6280771*i*	.95141
.3704988 + .8687226*i*	.94443
.3704988 - .8687226*i*	.94443
.7797765 + .5145006*i*	.934217
.7797765 - .5145006*i*	.934217
.1991507 + .9106038*i*	.932127
.1991507 - .9106038*i*	.932127
-.8316497 + .4061463*i*	.925525
-.8316497 - .4061463*i*	.925525
-.7893935 + .4829969*i*	.925434
-.7893935 - .4829969*i*	.925434
-.4619 + .7945385*i*	.919045
-.4619 - .7945385*i*	.919045
-.3246941 + .8570796*i*	.916522
-.3246941 - .8570796*i*	.916522
-.7544788 + .5190066*i*	.915754
-.7544788 - .5190066*i*	.915754
.02489615 + .9153424*i*	.915681
.02489615 - .9153424*i*	.915681
.6278731 + .6616136*i*	.912117
.6278731 - .6616136*i*	.912117
-.9073018 + .09284433*i*	.91204
-.9073018 - .09284433*i*	.91204
-.560833 + .7054974*i*	.901255
-.560833 - .7054974*i*	.901255
.8989565 + .04817208*i*	.900246
.8989565 - .04817208*i*	.900246
.5503641 + .7123116*i*	.90016
.5503641 - .7123116*i*	.90016
.1928122 + .8767872*i*	.897737
.1928122 - .8767872*i*	.897737
-.8578413 + .2235939*i*	.886502
-.8578413 - .2235939*i*	.886502
.8349977 + .2726971*i*	.878399
.8349977 - .2726971*i*	.878399
-.04810378 + .8621058*i*	.863447
-.04810378 - .8621058*i*	.863447
-.8593897	.85939
-.8320444 + .1505442*i*	.845554
-.8320444 - .1505442*i*	.845554
-.6142063 + .5775118*i*	.843071
-.6142063 - .5775118*i*	.843071
-.1915952 + .7786227*i*	.801849
-.1915952 - .7786227*i*	.801849
.2836065 + .690065*i*	.746071
.2836065 - .690065*i*	.746071
-.17455 + .692687*i*	.714341
-.17455 - .692687*i*	.714341
.3076169 + .5388996*i*	.620517
.3076169 - .5388996*i*	.620517
.2525097	.25251

All the eigenvalues lie inside the unit circle.
VAR satisfies stability condition.

Figure B.1: Stability condition for 7-lag model

Table B.2: VAR Residual Normality Tests

VAR Residual Normality Tests
Orthogonalization: Cholesky (Lutkepohl)
Null Hypothesis: residuals are multivariate normal
Date: 07/17/11 Time: 17:08
Sample: 2002M11 2011M06
Included observations: 91

Component	Skewness	Chi-sq	df	Prob.
1	-0.511388	3.966344	1	0.0464
2	-0.150893	0.345327	1	0.5568
3	-0.087872	0.117109	1	0.7322
4	0.202746	0.623439	1	0.4298
5	0.279628	1.185912	1	0.2762
6	0.096340	0.140769	1	0.7075
7	0.204707	0.635557	1	0.4253
Joint		7.014457	7	0.4274

Component	Kurtosis	Chi-sq	df	Prob.
1	4.120674	4.761993	1	0.0291
2	3.362374	0.497902	1	0.4804
3	2.764553	0.210193	1	0.6466
4	2.954297	0.007920	1	0.9291
5	3.241924	0.221916	1	0.6376
6	3.604133	1.383870	1	0.2394
7	3.326289	0.403678	1	0.5252
Joint		7.487472	7	0.3799

Component	Jarque-Bera	df	Prob.
1	8.728337	2	0.0127
2	0.843229	2	0.6560
3	0.327302	2	0.8490
4	0.631359	2	0.7293
5	1.407828	2	0.4946
6	1.524639	2	0.4666
7	1.039235	2	0.5947
Joint	14.50193	14	0.4130

Table B.3: VAR lag exclusion Wald tests

VAR Lag Exclusion Wald Tests
Date: 07/19/11 Time: 09:21
Sample: 2002M11 2011M06
Included observations: 91

Chi-squared test statistics for lag exclusion:
Numbers in [ ] are p-values

	NPL	CAPACITY	SPREAD	INDUSTRY	INDEBT	CLI1	EXPAN	Joint
Lag 1	69.33993	46.44376	45.20685	58.49114	59.87020	54.90953	15.86034	507.1104
	[2.01e-12]	[7.16e-08]	[1.25e-07]	[3.02e-10]	[1.60e-10]	[1.55e-09]	[0.026423]	[0.000000]
Lag 2	10.15599	12.64031	10.83236	10.37492	10.59088	24.63348	10.30889	154.0539
	[0.179904]	[0.081372]	[0.146101]	[0.168304]	[0.157487]	[0.000881]	[0.171734]	[8.67e-13]
Lag 3	18.68825	6.856227	9.590241	9.382237	5.288271	27.84151	11.46545	124.1374
	[0.009222]	[0.444002]	[0.213007]	[0.226365]	[0.624830]	[0.000235]	[0.119565]	[1.89e-08]
Lag 4	6.676024	10.07973	3.981324	5.895864	12.50676	15.38662	3.444439	76.08079
	[0.463373]	[0.184100]	[0.781926]	[0.551960]	[0.085078]	[0.031351]	[0.841075]	[0.007875]
Lag 5	10.15006	4.261524	13.13666	6.452048	6.900554	18.06857	5.046341	77.87633
	[0.180228]	[0.749210]	[0.068848]	[0.488064]	[0.439307]	[0.011664]	[0.654308]	[0.005395]
Lag 6	7.608984	7.111091	15.63292	3.682683	1.285855	15.48917	6.490402	66.02712
	[0.368332]	[0.417406]	[0.028690]	[0.815514]	[0.988814]	[0.030216]	[0.483790]	[0.052717]
Lag 7	5.375263	8.525885	19.60517	7.012093	12.75145	17.36050	6.690896	87.57599
	[0.614269]	[0.288510]	[0.006489]	[0.427622]	[0.078401]	[0.015214]	[0.461757]	[0.000586]
df	7	7	7	7	7	7	7	49

APPENDIX C: DYNAMIC FORECAST

Table C.1: Diebold-Mariano test for CLI1 vs. NPL AR models

Diebold-Mariano forecast comparison test for actual : lognpl	
Competing forecasts: "NPL_AR_lognpl" versus "CLI1_70_lognpl" Criterion: MAPE over 33 observations Maxlag = 9 chosen by Schwert criterion Kernel : uniform	
Series	MAPE
NPL_AR_lognpl	0.1350
CLI1_70_lognpl	0.0769
Difference	0.0580
By this criterion, "CLI1_70_lognpl" is the better forecast	
H0: Forecast accuracy is equal.	
S(1) = 2.986 p-value = 0.0028	

Table C.2: Diebold-Mariano for CLI1 vs. All CLI models for after 70th period

Diebold-Mariano forecast comparison test for actual : lognpl Competing forecasts: NPL_AR_lognpl versus CLI_1_3_lognpl Criterion: MAPE over 33 observations Maxlag = 9 chosen by Schwert criterion Kernel : uniform	
Series	MAPE
NPL_AR_lognpl	0.135
CLI_1_3_lognpl	0.06544
Difference	0.06952
By this criterion, CLI_1_3_lognpl is the better forecast	
H0: Forecast accuracy is equal.	
S(1) = 3.106 p-value = 0.0019	

Table C.3: RMSPEs for different model specifications

AFTER 75(February 2002) RMSPE (Percentage Error)					
after75ALL lognpl	CLI_1 after75 lognpl	CLI_3 after75 lognpl	after75 ONLYcli lognpl	after75 NO_cli lognpl	NPLonly after75 lognpl
0.0132313	0.07674	0.04698	0.047808	0.08625	0.09054

For the period starting from December 2009 (seventy fifth in the data) RMSPE (Root Mean Square Percentage Error) is calculated with different model specifications. Another model we compared with our model is the model which we used only CLI 3. CLI 3 model also has a better RMSPE than NPL-AR model. Again when we conduct Diebold-mariano test our base model statistically is a better model for forecasting. This can be explained by the construction method of CLI's for Turkey.[18] The 3 different CLI's are not substitute but they are complementary. Thus when we use all 3 CLI's in our model, statistically it has a significant improvement on forecasting.

[18] For a detailed explanation of CLI of Turkey see, Atabak, Coşar, Şahinöz (2005)

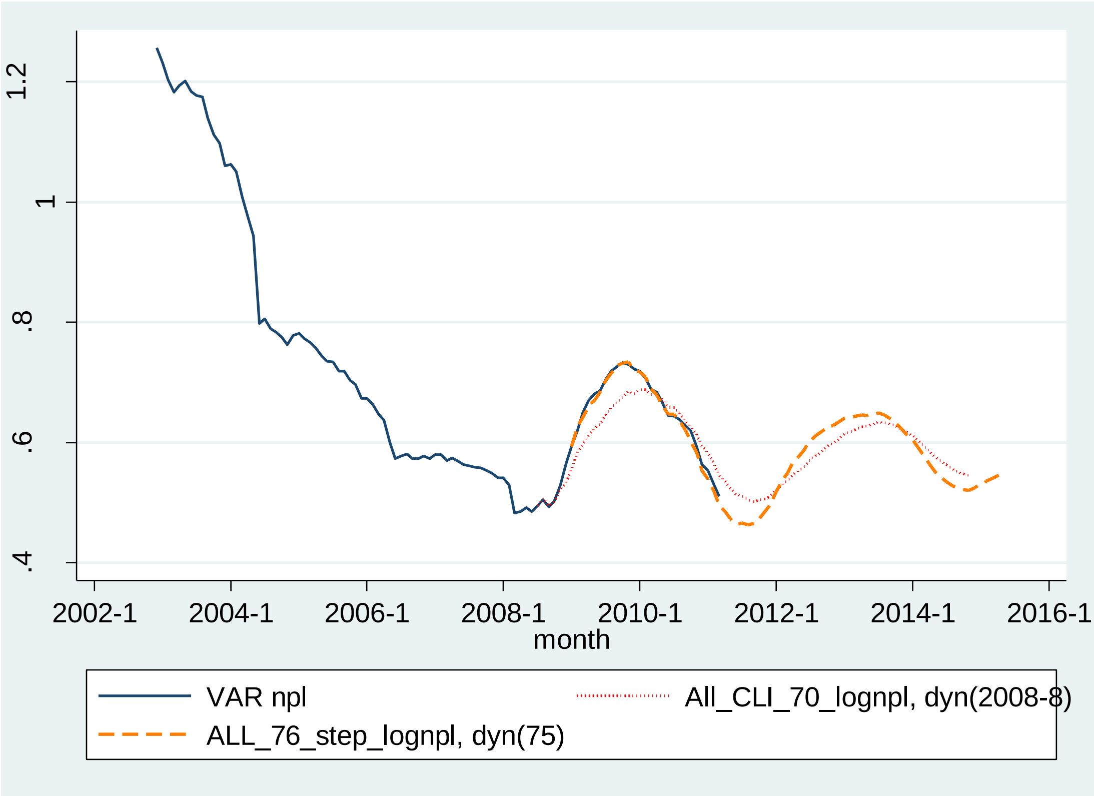


Figure C.1: The forecast accuracy for ALLCLI model

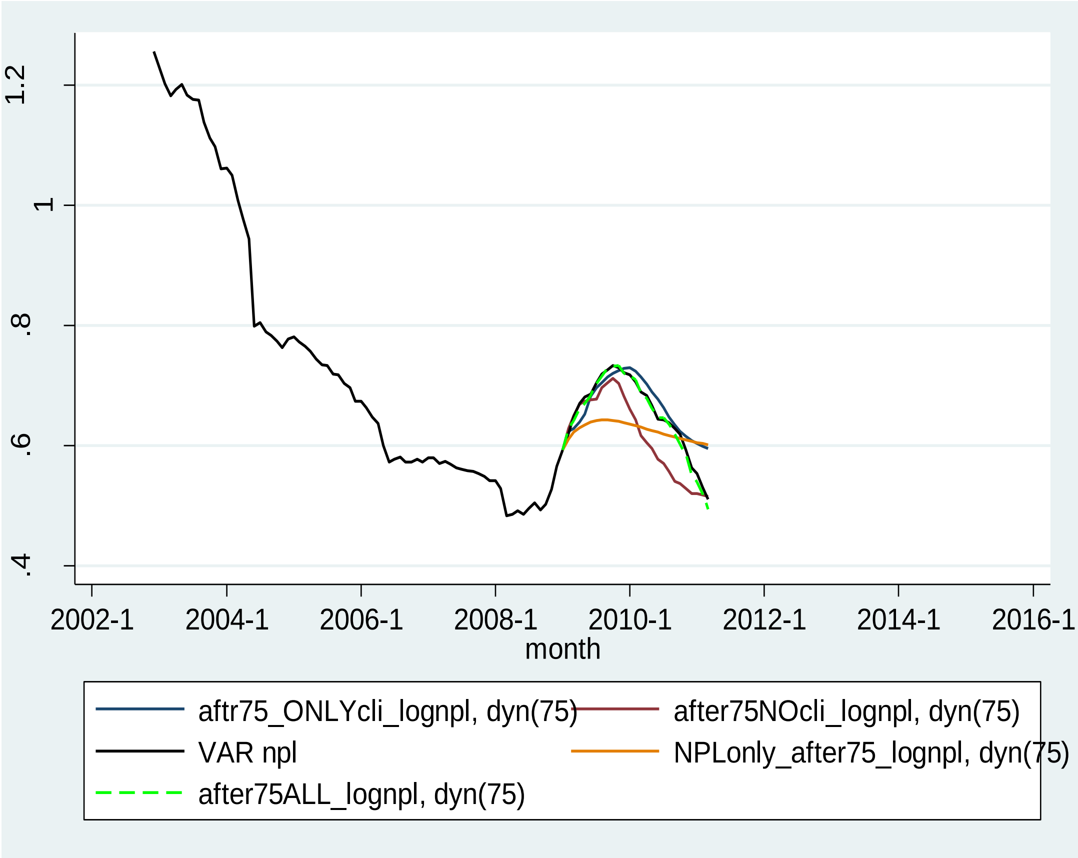
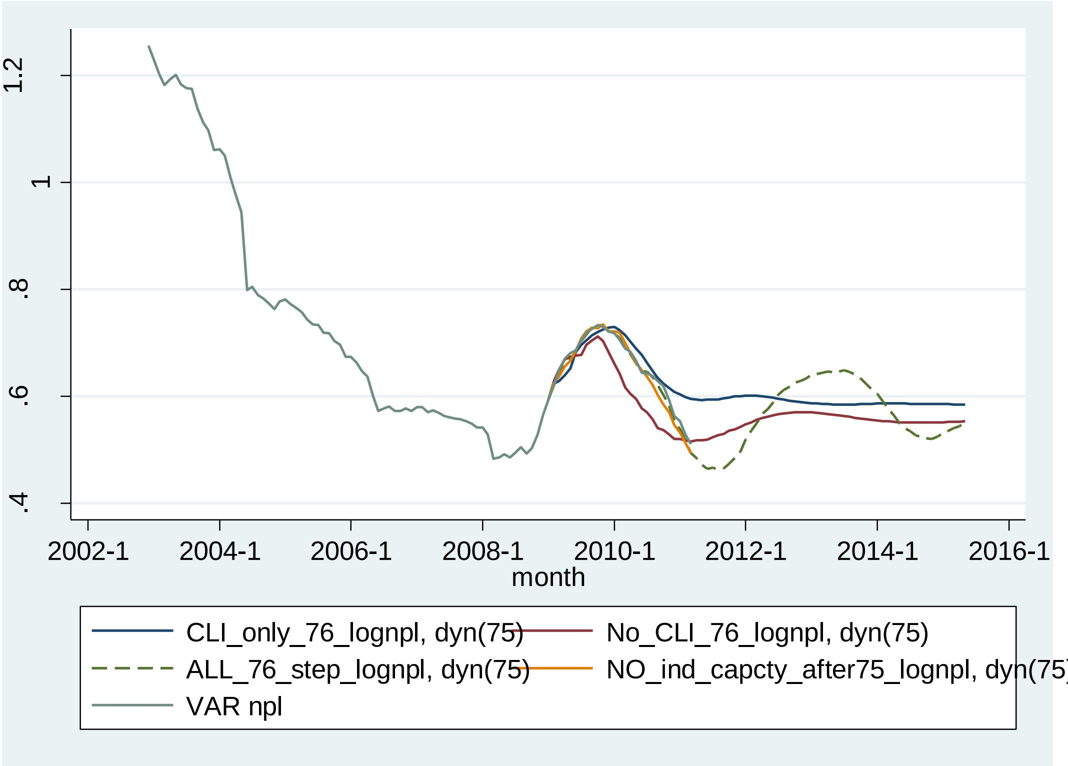


Figure C.2: Forecast results for different specifications



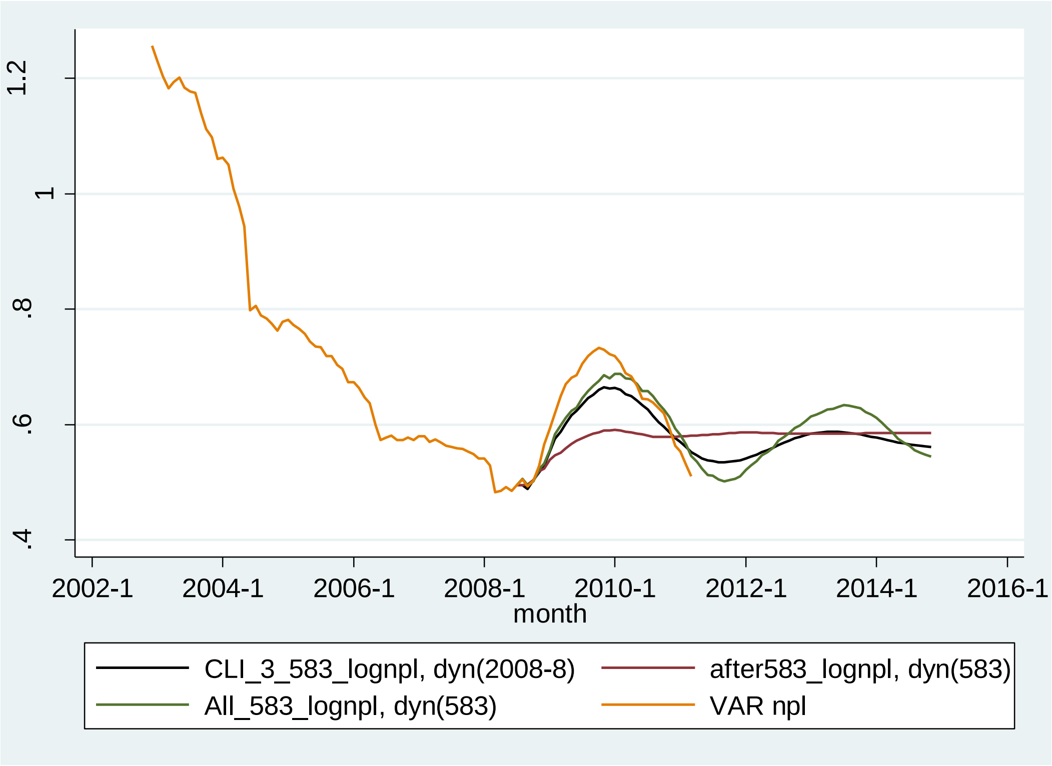


Figure C.3: Forecast results for different specifications

APPENDIX D: IMPULSE RESPONSE ANAYLSIS

Table D.1 : Accumulated Response of NPL to cholesky one standard deviation innovations

Period	NPL	CAPACITY	SPREAD	INDUSTRY	INDEBT	CLI1	EXPAN
1	0.013312	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
2	0.026791	0.002971	0.005770	-0.003719	-0.004836	-0.001729	6.60E-06
3	0.038856	0.003131	0.015414	-0.011985	-0.018491	-0.004528	-0.004411
4	0.053939	0.007586	0.027217	-0.023706	-0.034001	-0.007479	-0.008782
5	0.069530	0.010789	0.041139	-0.037986	-0.052284	-0.012293	-0.011532
6	0.085826	0.016398	0.054311	-0.052488	-0.072312	-0.014244	-0.013719
7	0.102463	0.023613	0.064191	-0.068388	-0.091231	-0.019286	-0.021298
8	0.118390	0.029340	0.074727	-0.085204	-0.107424	-0.023668	-0.027794
9	0.134876	0.032288	0.081878	-0.106035	-0.125342	-0.028907	-0.035059
10	0.152755	0.035858	0.088250	-0.126730	-0.140110	-0.033376	-0.042491
11	0.168762	0.039272	0.093449	-0.147028	-0.154532	-0.037908	-0.050003
12	0.182375	0.044705	0.096357	-0.165443	-0.171965	-0.041188	-0.055977
13	0.194999	0.051700	0.098293	-0.179741	-0.186102	-0.043921	-0.060310
14	0.204280	0.059202	0.098067	-0.192497	-0.200106	-0.044848	-0.063946
15	0.212089	0.066511	0.095612	-0.201244	-0.213385	-0.044396	-0.066991
16	0.218263	0.072880	0.092072	-0.206812	-0.222690	-0.044098	-0.070869
17	0.222817	0.076550	0.087921	-0.210998	-0.229399	-0.042908	-0.075347
18	0.226152	0.079125	0.082730	-0.211671	-0.233899	-0.040412	-0.078686
19	0.227363	0.079627	0.076640	-0.210009	-0.235127	-0.038515	-0.082278
20	0.226036	0.079691	0.070281	-0.206159	-0.234446	-0.036283	-0.084415
21	0.223224	0.079008	0.062842	-0.200011	-0.233037	-0.034401	-0.085093
22	0.219165	0.077942	0.055603	-0.192124	-0.229362	-0.032746	-0.085160
23	0.213665	0.076703	0.048403	-0.184087	-0.224906	-0.030739	-0.085086
24	0.207625	0.075350	0.041386	-0.174882	-0.220277	-0.028531	-0.084435
25	0.201793	0.073452	0.035199	-0.164902	-0.214287	-0.026568	-0.083512
26	0.195462	0.071596	0.029431	-0.155162	-0.208053	-0.024033	-0.082629
27	0.188906	0.069532	0.023902	-0.144390	-0.201697	-0.021456	-0.081447
28	0.182057	0.067122	0.018929	-0.133598	-0.194730	-0.019647	-0.080279
29	0.174962	0.064417	0.014494	-0.124084	-0.187971	-0.018178	-0.079092
30	0.168206	0.061724	0.010511	-0.114760	-0.181427	-0.016868	-0.077617
31	0.161941	0.058742	0.007157	-0.106422	-0.174857	-0.016090	-0.076489
32	0.155915	0.056096	0.004608	-0.099253	-0.168786	-0.015180	-0.075262
33	0.150582	0.053734	0.002471	-0.092454	-0.163466	-0.014349	-0.073795
34	0.146052	0.051686	0.000994	-0.086257	-0.158504	-0.013730	-0.072379
35	0.141879	0.050018	1.31E-05	-0.081126	-0.154386	-0.013026	-0.071144
36	0.138177	0.048617	-0.000599	-0.076474	-0.151201	-0.012548	-0.070058
37	0.135292	0.047161	-0.000530	-0.072795	-0.148427	-0.012582	-0.069254
38	0.132915	0.045837	7.45E-05	-0.070535	-0.146473	-0.012649	-0.068720
39	0.131212	0.044714	0.000980	-0.068911	-0.145276	-0.012814	-0.068346
40	0.130176	0.043763	0.002284	-0.068053	-0.144402	-0.013272	-0.068170

Cholesky Ordering: NPL CAPACITY SPREAD INDUSTRY INDEBT CLI1 EXPAN

Table D.2: Accumulated Response of Scenario Shock on NPL

Period	Accumulated effect	Period	Accumulated effect
1	0	21	0.029425
2	0.000904	22	0.027615
3	0.003163	23	0.025776
4	0.00571	24	0.023782
5	0.009082	25	0.021823
6	0.011959	26	0.019886
7	0.014833	27	0.01784
8	0.017986	28	0.015936
9	0.021745	29	0.014319
10	0.025293	30	0.012781
11	0.028698	31	0.01151
12	0.031334	32	0.010437
13	0.0331	33	0.009433
14	0.034258	34	0.008561
15	0.034549	35	0.007842
16	0.034392	36	0.007219
17	0.034169	37	0.006841
18	0.033352	38	0.006705
19	0.032366	39	0.006675
20	0.031058	40	0.006798
User Specified (SOK_CLI1)			

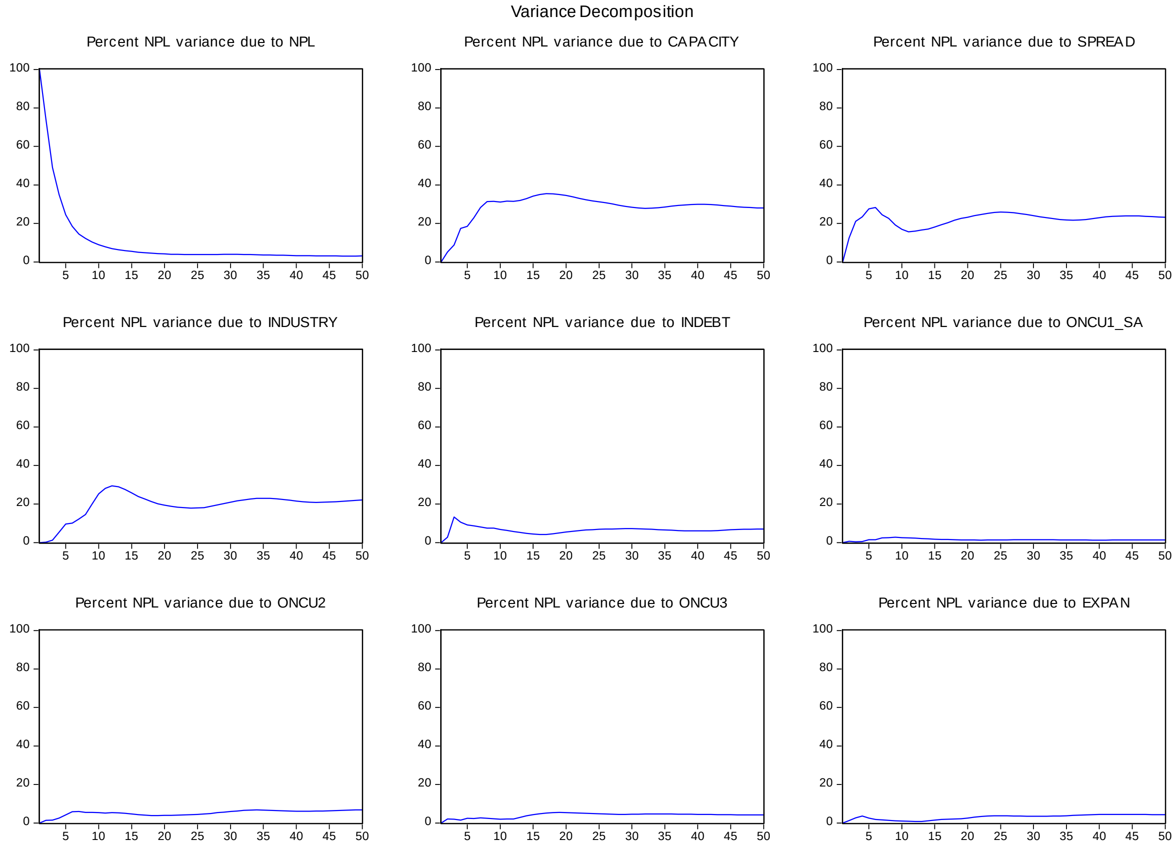


Figure D.1: Variance decomposition for NPL equation of VAR model

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