A STRESS TESTING FRAMEWORK FOR THE TURKISH BANKING SECTOR: AN AUGMENTED APPROACH

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ABSTRACT

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This thesis proposes a suite of models, which are a set of independent but complementary models, for conducting a macro stress test of credit risk for the Turkish banking sector. First model links financial stability to macroeconomic stability and estimates the relationship between macroeconomic variables and macrofinancial variables within a VAR framework. Second model employs static and dynamic panel data techniques to regress nonperforming loans to these macroeconomic and macrofinancial variables. With a view to the possible nonlinearities inherited in macroeconomic and financial series, nonlinear VAR and panel data models are considered. We also use alternative scenarios to test resilience of the banking sector. In a nutshell, we find that nonlinear models perform better than linear models and the banking sector is resilient to external shocks under the proposed scenarios.

Keywords: Stress test, Turkish banking, VAR, panel data, nonperforming loans.

ÖZ

TÜRK BANKACILIK SEKTÖRÜ İÇİN BİR STRES TESTİ ÇERÇEVESİ: BİR GENİŞLETİLMİŞ YAKLAŞIM

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Türk bankacılık sektörünün kredi riskine yönelik bir makro stres testi geliştirmek üzere tezde, bağımsız ancak birbirini tamamlayıcı set olarak bir modeller dizisinin kullanımı önerilmektedir. İlk olarak, bir VAR modeli çerçevesinde, finansal istikrarın makroekonomik istikrarla bağlantısı kurularak makroekonomik değişkenlerle makrofinansal değişkenler arasındaki ilişki tahmin edilmektedir. İkinci olarak, statik ve dinamik panel veri teknikleri kullanılarak tahsili gecikmiş alacaklar, söz konusu makroekonomik ve makrofinansal değişkenler aracılığıyla tahmin edilmektedir. Makroekonomik ve finansal değişkenlerin doğrusal olmayan olası karakteristikleri göz önünde bulundurularak doğrusal olmayan VAR ve panel veri modelleri de kullanılmaktadır. Bankacılık sektörünün sağlamlığını değerlendirmek için çeşitli senaryolar oluşturulmaktadır. Sonuç olarak, doğrusal olmayan modellerin daha iyi sonuç verdiği ve oluşturulan senaryolar altında bankacılık sektörünün dışsal şoklara karşı sağlam olduğu görülmüştür.

Anahtar Kelimeler: Stres testi, Türk bankacılık sektörü, VAR, panel veri, tahsili gecikmiş alacaklar.

To my lovely, joyful companion, Nilgün

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INTRODUCTION

The systemic nature of the global crisis, in the sense that it is contagious both within and across borders, increased the importance of macroprudential policies. After the global crisis of 2008, it is well understood that it is not possible to establish a better system simply by expanding the coverage of current regulation framework. Microprudential tools (such as capital and liquidity requirements) are inadequate in both detecting excessive risk taking behaviors and, hence, in preventing accumulation of weaknesses in the financial system. Moreover, some of these regulatory tools, in fact, worsen the situation by magnifying the procyclical tendency in the system. Therefore, in such a financial environment, internal weaknesses often may turn into a full-fledged crisis in the existence of a trigger event such as external shocks.

The systemic risks involve two factors to be dealt with: build-up of risks and exogenous shocks, and hence contagion. Borio (2011) classifies these factors, as dimensions of macroprudential policies, into two groups: time dimension and cross-sectional dimension. In this sense, time dimension corresponds to the procyclicality of the financial system that reflects mechanisms inherent to the financial system. On the other hand, cross-sectional dimension implies the interlinkages and common exposures in the financial system. From each source of financial distress, a policy principle can be extracted.

In line with the recent developments in the financial markets and the realm of policy making, new approaches appears to be introduced into the models for monitoring and measuring of risks in the financial system. Also both in national and international fora, a series of efforts are underway in order to upgrade existing financial regulatory frameworks. To this end, aftermath the eruption of the global crisis, G-20 organized a series of initiatives, and asked *FSB (Financial Stability Board)* and *BIS (Banking for International Settlement) Basel Committee on Banking Supervision (BCBS)* to work on new international banking standards. Within this framework, by gathering experts and policy makers from related financial authorities in G-20 countries, these institutions prepared a set of new rules, which are to be augmented to or revise the current Basel II regulations. Strengthening quality and quantity of capital (i.e. well defined capital and higher minimum capital ratio), capital buffers (expected to move countercyclically over time), setting a leverage ratio (to curb over-borrowing) and liquidity ratios are covered in this set of rules, which are directly related to the soundness of financial system.

We have also seen regulatory efforts within borders by countries. United States is among the early riser countries, in which Dodd-Frank Act legalized after the crisis. There are also certain initiatives in the EU towards a sound framework for regulation and surveillance of financial threat and for effective crisis resolution mechanism. To this end, EU Commission's de Larosiere Report (2009) recommends a macro-prudential task for the ECB, and this task covers mainly three issues:

i. Financial stability. It is now widely believed that macroprudential policies and countercyclical tools are needed to safeguard the financial stability.

ii. Early warning system (EWS). In order to monitor the threats arisen from financial fragility, it is stressed that the effectiveness of EWS should be increased. EWS aims to produce timely signals on probability of distress of whole banking system for policy makers, who may take preemptive measures against crises.

iii. Macro stress testing: In order to measure effects of exogenous shocks on overall banking system, we need to use macro stress testing.

In a nutshell, for an effective crisis prevention framework to be put into implementation, policy makers should make sure that following mechanisms are in place: macroprudential policies and tools which put emphasis on the overall stability of the financial system, an effective EWS to detect fragilities and measure degree of distress of the banking sector, and macro stress tests to measure the strength of the sector to external shocks.

The recent global crises emphasized the importance of system wide, called macroprudential, policies and shed the light on the missing parts of aforementioned tools to be combined more effectively in order to produce more efficient results against financial threats. IMF, BIS, FSB (2009) defines systemic risk as “a risk of disruption to financial services that is (i) caused by an impairment of all or parts of the financial system and (ii) has the potential to have serious negative consequences for the real economy”. IMF (2011) defines macroprudential policy as “a policy seeking to limit systemic, or system-wide, financial risk and argues that the prime objective of macroprudential policy is to limit build-up of system-wide financial risk”. Considering the immediate lessons from the ongoing crisis and in turn, transformation in current surveillance mechanism for financial threats, both national authorities and international institutions started to put more emphasis on system wide approaches and focus on mainly on EWS, procyclicality and macro stress-testing.

In this regard, for instance, some central banks (e.g. UK, Norway and Austria) already started to work on these areas and combine these tools via a suite of models. By adopting an eclectic approach, a macro stress testing (Vector Auto Regression-VAR) model linked to a probability of default model either of a bank and/or firms. Hence, it becomes more convenient to measure interactions between financial system and real economy. In this sense, a VAR model, without considering too much on issues about theoretical articulation, may provide efficient and reliable estimates and also necessary macroeconomic simulations, which is required for stress testing the financial system. In turn, it is possible to size feedback effects from stressed banking sector balance sheets to real economy via augmenting macroeconomic model by one more equation representing aggregated indicator of financial system.

In practice, academic and professional papers put more weight on measuring credit risk due to the share of credit risk (that is, counterparty default risk) in overall banking sector riskiness. And, generally, credit risk is estimated by panel data techniques on bank-by-bank or sectoral basis, that is based on type of loans such as mortgage or corporate loans etc. Due to the cyclicality of bank lending that behaves in line with economy's overall movement, ceteris paribus economic cycle indicators have sizeable share in explaining credit riskiness of banks. An alternative approach is to start with estimating conditional probability of banks' defaults on macroeconomic and individual indicators instead of concentrating on particular portion of overall riskiness. Such an approach may be more advantageous since any effort put on estimating probability of defaults may inherently be equivalent of identifying early warning indicators. This is important mainly because proactive policies and preemptive measures are vital against financial instability and these efforts are effective as long as they based on sound jurisdictions. No doubt, this requires a well-defined and integrated quantitative framework in monitoring and assessing developments in financial system.

Worrell (2004) suggests, in this sense, an assessment strategy designed to make best use of the available quantitative techniques in a complementary way. These techniques include early warning systems for financial distress; methods for sensitivity analysis and scenarios incorporated into stress test framework and financial forecasts. Sorge and Virolainen (2006) also emphasize the importance of such an integrated approach. And they draw a line between stress tests and early warning systems, emphasizing that the latter mainly focuses on estimating the probability of crises, while the earlier is used to evaluate the resilience of the financial system in the event of a crisis. Also, in this framework, it is important to specifically know how long banks can keep their resilience up against financial distress, probably due to an exogenous shock, until the shock hampers their ordinary activities. Therefore, the analysis of estimating sensitivity of capital buffer (or provisions) to economic cycle and its persistence can also be complemented to integrated framework.

This thesis proposes a suite of models for conducting macro stress test of credit risk. We employ both linear and nonlinear VAR models to forecast the future values of macroeconomic and macrofinancial variables, namely industrial production, consumer price index, interbank overnight deposit rate and banking sector total loans. Then, we use these forecasted values, which are obtained from the linear and nonlinear VAR models, in the panel data models to predict future values of the nonperforming loans of the banks, which is a proxy variable for the credit risk of banks. Hence, the main aim is to predict nonperforming loans of the Turkish banking sector. To do this, we adopt a cautious approach and employ several models including, linear fixed effects, random effects, dynamic fixed effects and nonlinear fixed effects models.

By comparing the predicted values and the actual values of the nonperforming loans, we can evaluate which panel data model delivers superior prediction performance for credit risk by employing several measures such as root mean square error, mean absolute percentage error and vice versa. Such approach also allows us to conclude which VAR model produces more precise forecasted values and whether a linear or a nonlinear VAR model structure should be adopted. Hence, we make a decision between linear and nonlinear VAR models based on an evaluation about their performance in producing good forecasted values. Therefore, it is worth to note that our main aim is not to choose the best VAR model, but find the best performing VAR model in forecasting the macroeconomic and macrofinancial variables since we primarily interested in obtaining forecasted values for macro indicators.

The empirical results show that nonlinear VAR and nonlinear panel data models provide better results, which proves our cautious approach on modelling right. This is also especially important that since earlier literature on macro stress testing ignores the nonlinear data generating mechanism, those studies may suffer from incompetence of providing reliable and accurate estimates and outcomes.

Illustration 1 provides an overview of a stress testing framework for the Turkish banking sector.

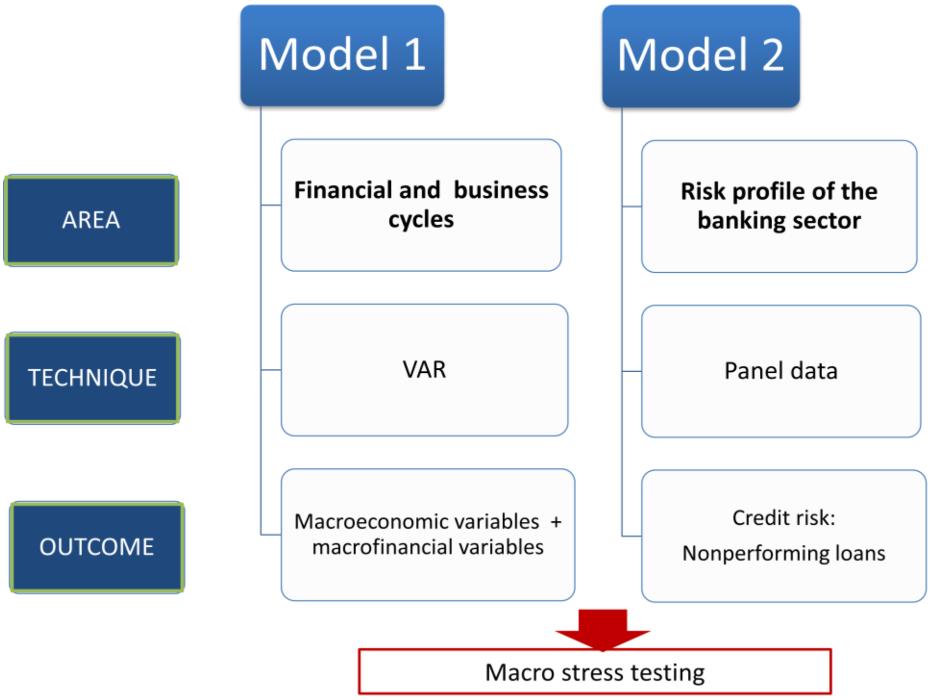

Illustration 1: Macro stress testing framework

This thesis aims to make several contributions to the literature. First, although there are studies inquiring the nonlinear features of macroeconomic and macrofinancial time series, this is the first study that employ nonlinear econometric methods in an integrated way in macro stress testing the banking sector. Second, as we discuss in detail in the second chapter, in literature macro stress studies either adopt VAR or panel data approach except few recent studies combining both techniques. Considering the existing stress testing studies in Turkey, this is the first time that VAR and panel data models are combined to analyze the resilience of the Turkish banking sector. Third, in addition to this combined approach, by this thesis, this is the first time that both VAR and panel data models are structured in nonlinear fashion.

The studies on macroeconomic modeling and measuring distress in the banking sector due to external shocks in general employ linear models. However, major macroeconomic and macrofinancial variables inherently reflect nonlinearities to some extent. The studies including Neftçi (1984), Hamilton (1989), Sichel (1993), Terasvirta and Anderson (1992), and Öcal and Osborne (2000) document evidence that many macroeconomic variables behave asymmetrically over different phase of business cycles, called cyclical asymmetry, and hence exhibit nonlinear dynamics. Hence, it is well documented that during an economic crisis macroeconomic variables decline sharply, but during upswings they do not recover at that pace.

Nonlinearity in financial system is a more recent topic in the literature and it has become popular especially after the recent global crisis. Accordingly, the financial system shows nonlinear dynamics to some extent since it is exposed to risk spillovers and negative externalities largely due to the interlinkages within the financial system. Accordingly, one institution imposes negative externalities on other institutions and on the whole system, for instance, liquidating its assets at fire-sale prices under a possible financial distress because of high leverage and excessive risk taking (Adrian and Brunnermeier, 2011). Also, the failure of a bank may produce a spillover effect in the system leading to negative externalities through the interlinkages among banks in interbank market or in payments and settlements system or by inducing an imperfect depositor migration (Acharya, 2009). As a result, although the contribution of the failure of a bank to systemic risk is linear considering its default probability, but it is nonlinear with regard to its size and asset correlation of all institutions in the portfolio (Huang et al, 2011). Therefore, as it is evident from the last global crisis, the transition of a financial system from a sound state to a distressed state could happen in a nonlinear fashion.

However, when applying a VAR or a panel data approach or combining both approaches in order to macro stress testing the banking sector, earlier studies disregard the nonlinear characteristic of macroeconomic and macrofinancial time series. Unlike existing literature, this study uses both nonlinear VAR and panel data models in order to capture the nonlinear characteristics of the employed time series.

The plan of the thesis as follows. Chapter 2 surveys the literature on the VAR models and panel data models. Here, we review the evidences on these models and how such models complement to each other. Taking a glance at the literature, macro stress testing practices are mostly exercised by adopting either a VAR or a panel data modeling approach. In practice, VAR models are employed to project macroeconomic variables, which are required for constructing the shock scenarios in stress testing the banking sector. Considering the fact that the balance sheet of the banking sector tends to move in parallel to economic cycles, VAR models may provide efficient and reliable estimates in considering the interaction between macroeconomic and macrofinancial variables. In line with the increased interest in the relationship between banking system and economic cycles, more and more effort put into modeling of this relationship to quantify the elasticities and size feedbacks from one to another. Whereas the VAR model focuses on the interaction between macroeconomic and macrofinancial variables and measuring the size of feedbacks from financial system to real economy, by a panel data model it is possible to analyze the risk profile of the banking sector by employing both macro and bank specific indicators. In literature, various studies are held in order to understand the relationship between asset quality, which is proxied by nonperforming loans or loan loss provisions, and business cycles.

In practice, considering the findings from the literature survey, studies mostly concentrate on aspects either dealing with the major interaction channels between banking sector and real economy or treating stress testing as an individual concept. In the latter case, the need for a macroeconomic scenario frequently is met by employing macroeconomic projections of an international institution like the IMF or another national institution (for example the macroeconomic model employed by a central bank). Only at few central banks, with one principal example of the model by the Bank of England, called RAMSI (The risk assessment model of systemic institutions), the macro stress testing studies are carried out on a more full-fledged basis.

In Turkey, in line with the increased efforts of evaluating the resilience of the banking sector, studies on the macro stress testing the Turkish banking sector have been carried out especially in the second half of 2000s. Considering the econometric method that they adopt, most of them employ a VAR approach in order to analyze the credit risk of the banking sector.

Chapter 3 take a brief look at the major developments and structural changes that occurred in the economy and the financial system during the analysis period, which covers the period after the 2000-2001 crises. With the introduction of The Transition to a Strong Economy Program, a new framework was adopted for both monetary and foreign exchange policies. The fiscal discipline and the improvement in the price stability outlook led to a decrease in interest rates and the Turkish lira appreciated. Investment and consumption preferences became more attractive due to the optimistic expectations under favorable economic environment. Also, with the restoration of the stability in financial markets and decreased macroeconomic uncertainties, the credit demand increased substantially. The fundamental and comprehensive restructuring measures enabled the banking sector to return its intermediary functions (such as granting loans to real sector), enhanced its strength against external shocks and upgrade its capacity towards sound risk management. Hence, during the analysis period, a fundamental change occurred in asset structure of the banking sector as banks allocate more resources for the real economy.

The crisis that started in US financial markets in August 2007 evolved into a global financial crisis in 2008, which resulted in adverse effects on the real economy and the financial system in Turkey. On the other hand, as they provide more favorable growth prospects and international funds searched for a higher yield around the globe, emerging markets including Turkey continued to attract massive capital inflows. As massive capital inflows fed into domestic credit and domestic demand, credit volume rapidly expanded, concerns on financial stability increased significantly. During the period after the global crisis, we observe that more proactive and extraordinary measures were adopted by the policy makers in Turkey in order to safeguard the financial and economic stability. Having a sound capital structure and a profitability performance, the Turkish banking sector is observed to be resilient to global fluctuations and external shocks during the period under review.

Chapter 4 discusses the model specifications. In order to conduct a macro stress test of credit risk, this chapter presents a suite of models, which are independent but complementary to each other. We first examine the relationship among macroeconomic and macrofinancial variables in order to reveal the interaction between the real sector and the financial system. First, we construct a linear VAR model. Then, with a view to the possible nonlinearities inherited in the macroeconomic and macrofinancial series, a nonlinear model is considered. Next, in order to find the macro and micro determinants of the asset quality of the banking sector, we employ panel data models. We regress nonperforming loans to macroeconomic and macrofinancial variables. Panel data models cover a range of models depending on whether it is static or not and whether it is linear or nonlinear. Hence, we start with static panel data models, i.e. fixed and random effects panel data models. In order to measure the persistency in nonperforming loans, a dynamic panel data model is also considered. Then, with a view to the nonlinearity in the financial systems, a nonlinear panel data model is taken into consideration.

Main purpose here is to stress nonperforming loans by using shocks to macroeconomic and macrofinancial variables within a one-month window. VAR model is mainly used to construct macro scenarios which represent external shocks for the financial system. To do this, we forecast macrofinancial and macroeconomic variables by using VAR model. Then, it is possible to measure the stress on the nonperforming loans, a measure for credit risk, due to external shocks to the financial system by employing forecasted macro indicators from the VAR model in the panel data model. We observe that nonlinear fixed effects panel data model perform well in forecasting nonperforming loans.

Chapter 5 introduces the empirical models i.e. the VAR and panel data models. This chapter mainly discusses the empirical results of the VAR and panel data models, which are explained in detail in Chapter 3. Within this context, the main aim of this chapter to predict nonperforming loans and macro stress test the Turkish banking sector under the proposed scenarios. The results of the VAR model suggest some evidence for first round effects, which works from the real sector through the financial system. Also, there is some significant finding for the second round effects (feedback effects) from financial system to the real side of the economy. We consider nonlinear dynamics in macroeconomic and macrofinancial variables as regime changes in overnight interest rates. The panel data models perform well in explaining the determinants of asset quality of banks. The empirical results suggest there is a significant interaction between macro indicators. And several macroeconomic and bank specific variables are good indicators in explaining developments in asset quality of banks. In the nonlinear fixed effects panel data model, as in the nonlinear VAR model, we find overnight interest rates as the most reasonable transition variable.

The major expectation from the macro model that is operationalized with a VAR specification is to produce macro scenarios, which then is used to measure effects of macro shocks on banks' asset quality. To do this, we forecast macrofinancial and macroeconomic variables by using VAR model. Then, by using the obtained forecasted values for the macroeconomic and macrofinancial variables and bank specific determinants of banks' asset quality, we calculate the nonperforming loans. These elasticities are obtained from linear fixed effects, random effects, dynamic fixed effects and nonlinear fixed effects models. We observe that the nonlinear VAR model performs best in forecasting macro indicators and the nonlinear fixed effects panel data model performs best in predicting the nonperforming loans of the banks. This finding is especially important that it reveals the inadequacy of the earlier literature, which ignores the nonlinear data generating mechanism. We should again remind that the decision for choosing the baseline model, i.e. linear vs. nonlinear structure, regarding VAR and panel data modelling does not based on the concern or the criteria of choosing the best model. But, instead, we decide whether a linear or nonlinear modeling structure is more preferable based on the findings about the performance of the models in forecasting or predicting the macro or micro time series.

Last, in order to test resilience of the Turkish banking sector, we use two alternative scenarios, which are composed of the shocks to macroeconomic and macrofinancial variables. In the first scenario, a shock to industrial production is considered, and the second scenario represents a sudden stop in credit growth. We calculate the deterioration in the asset quality proxied by the nonperforming loans and change in capital adequacy ratios. Accordingly, we find that the Turkish banking sector is resilient to such shocks.

CHAPTER 2

LITERATURE SURVEY

2.1 Introduction

Macro stress tests provide policy makers with information on potential losses of financial system under extraordinary but plausible scenarios. Stress testing of financial system is held in line with two alternative approaches: Bottom-up approach and top-down approach. Bottom-up approach requires stress testing a financial institution balance sheet by an external shock, which is mostly originated from real economy. Financial institutions and regulatory and supervisory institutions tend to give more credit such an approach since it provides clear-cut and to-the-point information. Although there is no inherent flaw in this approach, aggregated results of bottom-up approaches may underestimate the vulnerabilities that financial system is exposed to. The main reason for this underperformance is the ignorance of interaction between markets and institutions and cross correlation among asset classes, where the systemic risk comes to the fore. Especially just after the global crisis, in parallel to increased interest in macroprudential analyses, research in the area of top-down (i.e. macro) stress testing became more intensified and made progress to some extent.

Schmieder et al. (2011) call these brave new methods as “next generation stress testing” and identifies following four key properties of this new framework:

(1) integrated assumptions on shocks to run a series of scenarios;

(2) calculating the effect of the change in key risk factors due to the shocks on banks’ solvency,

(3) a user-friendly excel-like technical platform for stress testing,

(4) flexible framework to handle large panel set.

Foglia (2008) identifies three methodologies for macro stress testing, in which estimating effects of multiple shocks to macroeconomic and financial variables on financial sector are estimated using different models:

(1) a structural econometric model (for example models used by central banks for forecasting purposes),

(2) vector autoregressive models and methods,

(3) pure statistical approaches.

IMF (2012) proposes seven "best practice" principles for stress testing as practical guidelines derived from experiences, which accumulated deep practical experience through Financial Sector Assessment Programs (FSAPs) in member countries launched in 1999. IMF (2012) defines stress testing as a technique that measures the vulnerability of a portfolio, an institution, or financial system as a whole under different hypothetical events or scenarios. The principles are:

- Define the coverage of the stress testing properly. This implies that if the coverage of the whole financial system is not possible for system-wide stress tests, then it is reasonable to include systemically important institutions into the tests.
- Identify all risk propagation channels. This requires identifying and understanding the main channels of risk propagation.
- Consider all risks arisen from the activities of a financial institution. This requires understanding of the financial institution's business model and the market where it operates and learning its sectoral or cross-border exposures.
- Enrich stress testing framework by taking the perspectives of investors into consideration.
- Concentrate on tail risks. This implies the shocks to be used in stress test to be "extreme but plausible".

- When sharing stress test results with public, emphasize the critical points. This implies the communication of stress test with public and requires tailoring assumptions, methodologies, and results to circumstances and the goals of the tests.
- Beware of the "black swan". This implies the identification of potential tail events and requires evaluating the institutional coverage, risks, and channels of risk transmission.

IMF (2012) defines four types of stress testing methodologies based on their ultimate objective. The features of these methodologies are presented in Table 1. These methodologies are:

(1) An internal risk management tool: In order to evaluate the risks arising from their investments, financial institutions may employ stress testing as part of their internal risk management. Value-at-risk models can be given as example to this type of stress testing. The coverage of risk factors in such studies is, however, limited.

(2) Microprudential (supervisory) stress testing. The pillar 1 (minimum capital requirements) of the Basel II framework stipulates that banks should conduct stress testing for market risk and credit risk. Also pillar 2 (supervisory review process) of the Basel II framework authorizes supervisors to banks management to undertake additional tests.

(3) Macroprudential (surveillance) stress testing. Macroprudential stress tests focus on financial system as a whole and are employed to uncover the sources of systemic risk and vulnerability in the financial system.

(4) Crisis management stress testing. Stress tests are also useful tools for deciding the capital levels of financial institutions are adequate or not and whether they need to be recapitalized. This type of stress testing becomes increasingly popular especially after the global crisis of 2007-2009.

Table 1. Typology of Stress Tests				
Features	**Macroprudential (Surveillance)**	**Microprudential (Supervisory)**	**Crisis management**	**Internal risk management**
Main objective	Unveil the sources of systemic risk and vulnerability in the context of surveillance and regular system-wide monitoring.	Assess the health of an individual institution, inform supervision of the institution.	Input for bank recapitalization and business restructuring plans.	Manage risks from existing portfolio, input for business planning.
Organized by	Central banks, macroprudential authorities, IMF.	Supervisor (microprudential authority).	Macro and/or microprudential authorities.	Financial institutions.
Coverage of institutions	All, or as many as possible institutions, especially systemically important institutions.	Supervised individual institutions (tests for different banks could take place at different times).	Varies, but it should include all distressed and near-distressed institutions.	Individual institution.
Frequency	Typically annual or semiannual for country authorities, or in the context of Financial Sector Assessment Programs.	Individual institutions are tested as needed. Increasing number of supervisors conduct regular stress tests (with common assumptions).	As needed.	High (daily or weekly) for market risks, lower for enterprise-wide exercises.
Nature of shocks	Systemic and common shocks across institutions. Shocks tend to be extreme.	Often idiosyncratic; common macro assumptions are sometimes made for horizontal or thematic review across institutions.	Ongoing systemic stress (baseline) or relatively mild shocks, mainly focusing on solvency risks.	Idiosyncratic or systemic (those that matter for the particular institution).
Capacity to incorporate systemic risks	Through macro and market-level shocks and additional system-wide features (e.g., network effects).	Through macro and market-level shocks.	Through macro and market-level shocks.	Through macro and market-level shocks.
Likelihood of assumed shocks	Low.	Low.	High.	Varies.
Assessment criteria (hurdle rates)	Current or prospective regulatory requirements or alternative thresholds, if appropriate.	Current or prospective regulatory requirements or alternative thresholds, if appropriate.	Current or prospective regulatory requirements or alternative thresholds, if appropriate.	Internal risk tolerance indicators and regulatory requirements.
Key output metric	Aggregate indicators for the system, and their dispersion.	Individual institution indicators.	Individual institution indicators.	Individual institution indicators.

Table 1. Typology of Stress Tests (continued)				
Follow-up measures after tests	Typically no follow up for individual institutions, but often used as the basis for discussion of potential macroprudential or system-wide measures.	Institutions with weak results are often required to explain and take management actions if deemed necessary by supervisors.	"Failing" institutions are often required to take major management action, such as recapitalization, possibly with government support.	May or may not require management action.
Publication Main objective	Often. Unveil the sources of systemic risk and vulnerability in the context of surveillance and regular system-wide monitoring.	Rarely. Assess the health of an individual institution, inform supervision of the institution.	Varies. Input for bank recapitalization and business restructuring plans.	No. Manage risks from existing portfolio, input for business planning.

Source: IMF(2012)

Greenlaw et al. (2012) proposed principles for a macroprudential approach to stress tests on a more conceptualized ground. They view macroprudential macro stress tests as mechanisms focusing on whether the banking system as a whole has the balance sheet capacity, i.e. enough total capital, to support the economy. The proposed principles are:

- To avoid any possible run, banks should have enough capital.
- When the whole system fails to safeguard its stability, even solvent banks might face the danger of becoming depleting their capital. Therefore, supervisors should put more importance on overall stability of the system.
- It should be required to evaluate the lack of capitalization in dollar terms instead of capital ratios. And the critical point is the safeguarding sufficient capitalization, i.e. the equity level, of the whole banking system. Otherwise, focusing on capital ratios may encourage banks to deleverage after an external shock, which, in turn, may lead to a credit crunch.

- Therefore, in stress test studies, it is important to consider possible deleveraging activities and fire sales by banks as well as changes in the structure of liabilities.
- It is important to include liquidity rules into macroprudential monitoring activities in addition to capital requirements.

In the literature, in order to measure the vulnerability of the banking sector against external shocks, the macro stress testing studies adopt either a macro approach, which is mostly a VAR framework including macroeconomic and macrofinancial variables, or a micro approach, which aim to estimate the relationship between risk profile of the banking sector and macro and micro indicators. As mentioned before, an alternative approach to this common practice has been emerged after the global financial crisis and it links the framework of macro analysis to modeling of the risk profile by some central banks in advanced countries.

2.2 VAR Approach for the Interaction between Macroeconomic and Macrofinancial Variables

In literature, one stream of applied studies adopts a VAR framework in testing the vulnerability of the banking sector to external shocks (Table 2). Researchers may benefit from VAR models to project macroeconomic variables which are required for forming scenarios. Although these models do not represent the exact structure of the economy, they produce estimates, which are adequate to meet the needs, and are flexible to be expanded in order to obtain second round effects. However, as long as these models do not take into account the structural shifts in the data and are in linear structure, they may suffer from a poor forecast performance. Since the macro indicators, as noted before, may show nonlinear characteristics and the responses of macrofinancial variables to macroeconomic fundamentals may be nonlinear (Neftçi, 1984; Hamilton, 1989; Sichel, 1993;

Terasvirta and Anderson, 1992; Öcal and Osborne, 2000; Huang et al, 2011), this requires that some nonlinearity should be introduced in these models.

Macroeconomic variables gradually can affect banks' financial strength and their risk profiles and this effect may differ whether ordinary or stressed economic conditions prevail. Indeed, as it is evident from recent global crises, the efficient functioning of credit markets depends on to what extent money markets function effectively and efficiently. Structure of money market and credit markets also matter. For example, Becker et al. (2010) show that banks do not respond to marginal changes in money market interest rates and hence do not reflect these changes when setting the interest rates for loans, which leads to a two-stage transmission mechanism.

Virolainen (2004) and Avouyi-Dovi et al. (2009) stress test the financial systems respectively in Finland and France. Main distinctive feature of their approach is to relate the probability of default of firms, which is the counterparty risk for banks, to a macroeconomic index via a logistic function. By establishing the link between macroeconomic conditions and firms' financial soundness, Avouyi-Dovi et al. (2009) estimate a VAR model (GDP, interest rate, firms' borrowing spread and macroeconomic index) and Virolainen (2004) estimates industry specific macroeconomic index for six industries by a seemingly unrelated regression (SUR) model in order to calculate probability of defaults for these industries.

Similar studies implemented respectively for Germany and Sweden by De Graeve et al. (2008) and Jacobson et al. (2005). They link the macroeconomic conditions to banks' probability of defaults in a more integrated way. Jacobson et al. (2005) obtain projections for macroeconomic variables from an expanded standard monetary VAR model (GDP, interest rate, inflation and since Sweden is a small open economy, exchange rates) and banks' default rates from a logit model. Then they link macro-financial series by a dynamic panel data model. On the other hand, De Graeve et al. (2008) use a VAR model (GDP, interest rate, inflation and aggregated probability of defaults of banks as an exogenous variable) to project macroeconomic series and a survival model to estimate banks' default rates. In order to establish the linkage between macro-financial variables, they expand the VAR model by introducing the aggregated banks' probability of defaults as a fourth equation, which provides a convenient way to produce feedback effects from banking sector to real economy. Dovern et al. (2010) stress test the German banking sector for the period 1967-2007 and uses a Bayesian VAR model, in which GDP, interest rate, inflation and banking sector soundness indicators are used as endogenous variables and US GDP as an exogenous variables. Instead of estimating a separate model for banking sector soundness indicators, they use write-off rates and return on equity alternately.

On the other hand, Girault (2008) and Vazquez et al. (2010) adopt an alternative integrated approach, respectively for Argentina and Brazil, in which they use a dynamic panel model as well as a VAR model and to estimate credit risk on a panel set of banks. As a dependent variable, they use logit transformation of nonperforming loans for different loan segments, which is a proxy for probability of default. Assuming these countries are small and open economies and considering the variables (e.g.GDP growth, credit growth, and yield curve or overdraft interest rate) employed in VAR models, composition of VAR models for these countries significantly differ from the standard VAR models. As a next step, they combine the results of the estimation of these models through macro scenarios, constructed either through CreditRisk+ (Credit Suisse First Boston's risk management method), Monte Carlo or historical simulations.

There are also studies focusing on emerging and developing economies. Kattai (2010) estimates a regression of nonperforming loan and loan loss provisions for mortgage, consumption and corporate loans of largest banks in Estonia on macro fundamentals (unemployment, output, interest rate, credit growth, debt ratio) for the period 2003-2009. Macro fundamentals which are given in a logit form represent the sectoral probability of defaults and the logistic form introduces nonlinearity into the system. Kattai uses a VAR model (GDP, inflation, interest rates for different loan segments and unemployment) to obtain projections for macroeconomic variables.

In literature, instead of using panel data models as a common practice, some studies employ VAR models in order to estimate to the credit risk of the banking sector. Accordingly, researchers employ VAR techniques to investigate cyclicality and procyclicality issues for the financial system. In order to measure both the extent which the macroeconomy has influences on the balance sheet of the banking sector, called cyclicality, and the extent which, the banking sector's response to changing economic environment, in turn, affects the macroeconomy and amplifies its fluctuations, called procyclicality. Marcucci and Quagliariello (2006) investigate procyclical behavior of the default rates of Italian banks' borrowers over the period 1990-2004. They estimate a VAR model by employing the variables bank borrowers' default rate, output gap, inflation rate, 3-month interbank interest rate, real exchange rate. They find that the default rate is cyclical, that is, banks' portfolio quality tends to deteriorate during downturns. In addition to the evidence on the first round effect, they also find some support to the idea that a feedback effect from the banking sector to the macroeconomy operates via the bank capital channel.

Gambera (2000) employs bivariate VAR systems to investigate effects of macroeconomic factors on bank asset quality over the period 1987-1999. Gambera finds that measures of income (including farming income) and unemployment appear to be good predictors of problem loans.

Recently more sophisticated approaches for stress testing have been produced. Bank of England (Alessandri et al. 2008; Alessandri et al. 2009; Aikman et al., 2009) and Central Bank of Norway (Andersen et al., 2008) apply macro stress tests in a framework of a suite-of-models. Alessandri et al. (2008) use two country (small open economy, England and rest of the world, US) version global VAR model (GDP, inflation, short- and long-term interest rates, exchange rate and oil prices). Instead, Aikman et al. (2009) use a Bayesian VAR model (24 domestic and foreign variables, and three country and area: England, US and EU). For modeling first and second round effects of changes in macroeconomic variables on banking sector, both papers follow exactly the same approach, where they model probability of defaults for different loan segments, yield curve, trading income, net interest income, asset pricing and banks' interbank exposures (network model to consider contagion). Andersen et al. (2008) use a small structural model for Norwegian economy and three distinctive models to estimate probability of defaults for firms, households and banks, in which financial soundness of sectoral balance sheets are function of macroeconomic conditions.

Studies on macro stress testing the Turkish banking sector have started appear in the second half of the 2000s. Most of these studies adopt a VAR approach in order to analyze the credit risk of the banking sector. Küçüközmen and Yüksel (2006) evaluate resilience of the banking sector to external shocks on a sectoral basis. They, first, run eight OLS regression for different sectors for the economy to find out the determinants of nonperforming loans, a proxy for credit risk, on a set of macro indicators, namely, banking sector total loans, current account balance, gross national product, foreign exchange rate, interest rate, inflation and unemployment. Then for each macro indicator by estimating ARIMA their structures they derive correlation matrix. And last they stress nonperforming loans by using historical scenarios by simulating one step ahead nonperforming loan values.

Beşe (2007) investigates the relationship between nonperforming loans and macroeconomic variables, output gap, inflation, interest rate, real foreign exchange rate and emerging markets bond index. Instead of using nonperforming loans as a proxy for credit risk, Çanakçı (2008) uses a more general risk indicator, Z-score, a measure for banking sector distress and also employs return on equity as an alternative fragility indicator. Çanakçı employs a VAR model in order to estimate the relationship between these indicators and macroeconomic variables, credit to public sector, industrial production index, real exchange rate and interest rate and next produces simulations based on the VAR estimates and observes the changes in fragility measures.

Table 2. Literature on VAR models

	Country	Period	Model	Variables
Vazquez et al.	Brazil	2001-2009	Vector Auto Regression	GDP growth, credit growth , and changes in the slope of the domestic yield curve
Girault	Argentina	1994-2006	Vector Auto Regression	GDP growth rate, overdraft interest rate, the price of commodities, the sovereign risk and the federal funds rate
Dovern et al.	Germany	1968-2007	Bayesian VAR	GDP, CPI, interest rate, US GDP and banking sector soundness indicator (write-off or ROE)
De Graeve et al.	Germany	1995-2004	Vector Auto Regression	Output growth, CPI, 3 month interest rate, and aggregate Probabilty of default of banking sector
Jacobson et al.	Sweden	1986Q3–2002Q4	Vector Auto Regression	Output gap , inflation, interest rate, exchange rate, exogenous variables(foreign output gap, inflation, interest rate) and aggregate default frequency
Kattai	Estonia	1999Q3-2009Q2	Vector Auto Regression	Economic growth, inflation, mortgage int rate, consumption credit int rate, corporate credit int rate, unemployment rate

Table 2. Literature on VAR models (continued)				
Avouyi-Dovi et al.	France	1995Q1 - 2006Q4	VECM and VAR	GDP, interest rate, spread b/w corp and gov't int rate, and a macroeconomic index
Virolainen	Finland	1986Q1- 2003Q2	SUR model	GDP , money market interest rate , corporate indebtedness , and year dummy for law change
Andersen et al.	Norway		small macro model	house prices, household credit, GDP, banks' problem loans, enterprise credit
Alessandri et al.	England	1979Q1- 2005Q4	Global VAR	GDP, CPI, real equity prices, overnight nominal interest rate, 20-year nominal interest rate, exchange rate
Aikman et al.	England	1972Q2- 2007Q4	Bayesian VAR	24 domestic and foreign (US and EU) variables

Instead of combining macroeconomic and macrofinancial variables in a VAR setup, Sonbul İskender (2012) analyses the interaction among macroeconomic variables separately, GDP, inflation, external debt, interest rate, foreign exchange rate and unemployment rate, and then searches out the macroeconomic determinants of nonperforming loans and banking sector credit by an OLS regression.

In order to stress test the banking sector and obtain forecasted values for credit risk Aysan et al. (2014) employ a VAR model, by which they evaluate the effects of macroeconomic indicators on nonperforming loans. In the VAR model, Aysan et al. use industrial production index, capacity utilization rate, the ratio of banking sector loans to total assets, credit expansion, interest rate spread and a composite leading indicator as macro indicators in addition to nonperforming loans.

2.3 Panel Data Approach for Estimating Credit Risk

In literature the majority of studies on the stress testing framework from a micro perspective frequently go in hand with the analyses of the macroeconomic determinants of banking sector risk profile. Over time banks' balance sheets tend to move in parallel to economic cycles, which is the case coined as 'procyclicality' in financial system. On the other hand, materialization of the risks that banks face in general and credit risk in particular behaves countercyclically.

The term procyclicality is generally used to refer to the mutually reinforcing ("positive feedback") mechanisms through which the financial system can amplify business fluctuations and possibly cause or exacerbate financial instability (BIS, 2008).

Cyclically induced changes in taxes and government expenditures which tend to stabilize aggregate output are called automatic stabilizers (Scharnagl and Tödter, 2004). Likewise, in finance, it is needed to devise automatic stabilizers to function countercyclically in order to dampen adverse interaction between finance sector and the real side of economy especially under stress periods. Hence, just after the global financial crisis, the topic gains utmost importance as a macroprudential instrument for policymakers which concern with safeguarding the financial stability.

The key problem here for policy makers is that when the economic conditions are favorable the financial system has not set aside enough buffers to face the possible challenges ahead. At these times it is easier and cheaper to build up buffers and it also allows absorbing losses without shrinking the funds to real sector in harsh times. Unless the banking system has sufficient buffers, the system amplifies the economic shocks and exaggerates their contractionary effects. Therefore, a countercyclical regulatory system is needed to dampen asset booms and to smooth busting bubbles. In line with this, the BIS (2008) stipulated a general framework, in which dynamic provisions and capital buffers are proposed in order to strengthen banks' loss absorption capacity for, in respectively, expected and unexpected losses. Capital buffer is generally defined as the difference between current regulatory capital ratio and minimum required capital ratio.

The Basel Committee (BIS BCBS, 2011) agreed that a building block approach should be adopted to organize the work on procyclicality. The four key objectives identified were set out as follows on strengthening the resilience of the banking sector:

- conserve capital to build buffers at individual banks and the banking sector that can be used in stress; and
- achieve the broader macroprudential goal of protecting the banking sector from periods of excess credit growth.
- promote more forward looking provisions;
- dampen any excess cyclicality of the minimum capital requirement;

In line with the increased interest in the relationship between banking system and economic cycles, more and more effort put into modeling of this relationship to quantify the elasticities and size of feedbacks from one to another. Generally, a partial adjustment model is estimated on panel data set across banks to derive these elasticities, which may be, in a later stage, used to calculate the effect of stressed economic conditions. Since banks set aside returns to pile up their capital buffers or provisions, respectively for unexpected and expected losses, analysts and researchers tend to relate capital buffers or loan loss provisions (LLP), or directly loss itself i.e. nonperforming loans (NPL) with economic cycle, which, in practice, is proxied by GDP or industrial production.

There is a huge literature to understand the relationship between asset quality, which is proxied by loan loss provisions or nonperforming loans, and business cycle (Table 3).

Table 3. Literature on Panel Data Models

	Sample	Sample period	Impact of GDP growth	Interest rate	Credit growth	Equity/ Earnings	Memo
Beck et al. (2013)	75 countries	2000-2010	-ve	+ve			(1) Exchange rate depreciations have positive impact on non-performing loans. (2) A decline of stock prices can negatively affect bank asset quality.
Nkusu (2011)	26 advanced countries	1998-2009	-ve	+ve			(1) Unemployment has positive impact on non-performing loans. (2) A decline of stock and housing prices can negatively affect bank asset quality
Glen and Velez (2011)	22 major developing economies	1996-2008	-ve	+ve	+ve	-ve	
Espinoza and Prasad (2010)	80 Gulf Cooperation Council region banks	1995-2008	-ve	+ve	+ve	-ve	
Louzis et al. (2010)	9 Greek banks	2003-2009	-ve	+ve	insig	-ve	(1) Unemployment has positive impact on non-performing loans.
Quagliariello (2006)	207 Italian banks	1985-2002	-ve	+ve	-ve	+ve	

Table 3. Literature on Panel Data Models (continued)

Rinaldi and Sanchis-Arellano (2006)	7 euro area countries	1989 to 2004		+ve			(1) Unemployment and inflation has positive impact on non-performing loans. (2) Household indebtedness has positive impact on non-performing loans.
Salas and Saurina (2002)	Spanish commercial and saving banks	1985-1997	-ve		insig	-ve	

+ve=positive, -ve=negative, insig=insignificant.

To do this, researchers control either for bank specific effects or country specific effects. For instance, Beck et al. (2013) explains the differences in bank asset quality across countries and over time applying dynamic panel data model. Hence they study the empirical determinants of nonperforming loans ratios using a data set for 75 countries for the period from 2000 to 2010. The findings of their study suggest that real GDP growth was the main driver of nonperforming loan ratios during the past decade. They find that exchange rate depreciations lead to an increase of nonperforming loans in countries with a high degree of lending in foreign currencies. They also find that a decline of stock prices can negatively affect bank asset quality, in particular in countries with large stock markets relative to GDP. Finally, an increase in lending interest rates tends to increase nonperforming loans.

Adopting a similar approach, Glen and Mondragon-Velez (2011) analyzes the relationship between loan portfolio performance that is proxied by loan loss provisions and the business cycle for 22 major developing economies for the period

1996-2008. Their results indicate that while economic growth is the main driver of loan portfolio performance, interest rates have second-order effects. According to their findings, the data suggest a negative relationship between provisions and GDP growth and a positive relationship with lending rates. They also find that higher private sector indebtedness, individual banks or banking system leverage and accumulated loan loss reserves are associated with higher levels of loan loss provisions.

Similarly to Glen and Mondragon-Velez, Nkusu (2011) employs panel data techniques on a sample of 26 advanced countries over the period 1998 to 2009 in order to study the determinants of nonperforming loans and analyze the interactions between nonperforming loans and economic performance. They find that adverse shocks to asset prices, macroeconomic performance, namely GDP growth and unemployment, and credit to the private sector all cause loan quality to worsen. Regarding the feedback effects, their findings suggest that asset prices, credit to the private sector, economic growth, and nonperforming loan itself all worsen significantly in response to a nonperforming loan shock.

Another study evaluating the credit risk across different countries is by Bikker and Hu (2002). They analyze the interaction between business cycles and bank behavior proxied by loan loss provisions for 26 industrial countries over the period from 1979 to 1999. They find that provisions for credit losses to a large extent depend on the business cycle which is proxied by GDP growth, inflation and unemployment. Accordingly, the coefficients of GDP growth and inflation turn out to be significantly negative, while that of unemployment is significantly positive, implying that provisions increase during cyclical lows. They also find that in years of high net interest income i.e. in good years banks tend to reserve more as a precaution or for credibility. As a result of such countercyclical provisioning policy, bank behavior is less procyclical than would appear just from looking at their dependence on the business cycle.

Adopting a panel cointegration approach, Rinaldi and Sanchis-Arellano (2006) analyze the determinants of the household's nonperforming loan ratio, which they argue that it constitutes the best indicator available for household financial fragility. To do this they use panel data for seven euro area countries from 1989 to 2004. They find that in the long run a higher ratio of debt-to-income i.e. household indebtedness is associated with a higher level of nonperforming loans. They also find monetary conditions important because rising inflation and lending rates significantly worsen financial conditions. According to their findings, in the short-run the role of financial wealth and housing wealth (proxied by the house price index) tends to confirm the idea that wealth is used as a buffer in case of unexpected shocks.

Bouvatier and Lepetit (2008) investigate causes for fluctuations in bank lending in Europe. They employ a panel of 186 banks for the period 1992-2004 and use difference and system GMM techniques. They found out that nondiscretionary loan loss provisions that are mainly related to economic cycles amplify bank lending. In this sense, it is argued that dynamic provisioning may perform better in overriding the amplification in credit cycle. Bouvatier and Lepetit (2010) widen the scope of analysis by adopting a global approach. They employ panel data of 3040 banks from eight countries for the period 1995-2008. Their results are compatible with those in their previous work, so that backward-looking provisioning practices amplify the cyclicality of bank lending.

Instead of using a static panel data approach, Espinoza and Prasad (2010) estimates a dynamic panel model over 1995–2008 on around 80 banks in the Gulf Cooperation Council region in order to derive the relationship between macroeconomic variables and nonperforming loans as a proxy for credit risk in banks' books. According to findings of Espinoza and Prasad, the nonperforming loans ratio worsens as economic growth rate becomes lower and interest rates and risk aversion increase. They find that larger banks and banks with lower expenses would also have lower nonperforming loans. Besides high credit growth in the past could generate higher nonperforming loans in the future.

In literature, there are also studies concentrating on a single country in estimating the credit risk. Stolz and Wedow (2005) investigate the effect of economic cycle proxied four different indicators (federal and state real GDP growth rate, detrended GDP growth rate and output gap) on banks' capital buffers over the period 1993 to 2003 for German savings and cooperative banks. By estimating a dynamic panel data model by system GMM technique, they found out that banks' capital buffers behave countercyclically over economic cycles, and the fluctuation in risk-weighted assets are the main driver underlying this fact.

Boucinha (2008) investigates the determinants of Portuguese banks' capital buffers. Boucinha employs an unbalanced data of 17 banks for the period 1994-2004. Boucinha found out that there is a negative relationship between banks' capital buffer and economic cycle, and unsurprisingly, provisions and profit performance are substitutes for buffer.

Across different loan classifications, Louzis et al. (2010) analyze the determinants of nonperforming loans for nine largest Greek banks. To do this, they estimate a regression of the nonperforming loans on some macroeconomic variables, including GDP as a proxy for economic cycle, and observed and unobserved bank specific factors for the period 2003-2009. They estimate the dynamic panel data model by a difference GMM technique. It is found that GDP growth rate, unemployment rate and interest rate, and bank management indicators perform quite well in explaining banks' nonperforming loans.

In addition to the relationship between asset quality and business cycles, the cyclical behaviors of asset quality is also separately analyzed in literature. In this sense, Quagliariello (2006) analyze the Italian banking sector over the period 1985-2002 by employing both static and dynamic panel data models in order to investigate whether loan loss provisions and nonperforming loans show a cyclical pattern. They analyze cyclicality of loan loss provisions and nonperforming loans separately. They find that banks behave procyclically since loan loss provisions and nonperforming loans start to be recorded at the peak of the upturn and rise significantly during the subsequent recession. This is often coupled with a contraction of earnings. They also argue that as a feedback effect, banks tighten credit supply during downturns, thus further deepening the negative impact of the business cycle.

Salas and Saurina (2002) investigate the nonperforming loans of Spanish banking sector for the period from 1985 to 1997. In order to find out the determinants of nonperforming loans they investigate several macroeconomic and individual bank level variables. They conclude that credit risk proxied by nonperforming loans is significantly determined by microeconomic individual bank level variables. Accordingly, the growth policies of banks i.e. credit expansion or new market penetrations and their managerial incentives determine future loans losses.

Concentrating on the UK banking sector, Pain (2003) investigates cyclical influences on banks' loan loss provisions by using static and dynamic panel data techniques for the period 1978–2000. The author find that business cycle and changes in asset prices are important factors affecting bank provisioning due to the fact that they reflect the changes in the ability of borrowers to repay their bank debt. According to the findings of the study, GDP growth, interest rates and lagged aggregate lending are main factors determining banks' provisions. The author also finds that increased lending to riskier sectors, such as commercial property companies, has generally been associated with higher provisions.

Cavallo and Majnoni (2001) investigate whether cyclical shortages of banks' capital due to the lack of risk based regulation of banks' loan loss provisioning practices by panel data techniques. They analyze the period from 1988 to 1999 for 1176 banks from 36 countries. They find that the level of institutional development such as per capita GDP significantly affects loan loss provisioning practices and the positive association between loan loss provisioning and banks' earnings. But this relationship does not hold for banks located in non-G10 countries. They argue that this result is due to inadequate provisioning in booming and a capital regulation without sound provisioning rules may have procyclical effects.

Pesola (2005) analyzes the macroeconomic determinants of banking sector distresses proxied by nonperforming loans in the Nordic countries, Belgium, Germany, Greece, Spain and the UK by panel data techniques for the period from 1980s to 2002. They find that strong adverse aggregate shocks, proxied by income and real interest rates, basically leads to loan losses. They also find that the customer indebtness combined with adverse macroeconomic shocks results in financial distress in the banking sector.

Davis and Zhu (2005) analyze a sample of 904 banks worldwide over the period 1989–2002. They investigate the effect of changes in commercial property prices on loan loss provisioning. They find that commercial property prices have a significant effect on the behavior and performance of individual banks. They also find that the magnitude of this effect is related to the size of the bank, the strength of bank capital, the direction of commercial property price movements, and regional factors.

In general in theory, loan loss provisioning is considered to be procyclical if it rises during periods of economic downturns and recessions, and tends to fall during periods of high GDP growth. Arpa et al (2001) analyze the effects of macroeconomic developments on loan loss provisions of Austrian banks. They find that banks increase their loan loss provisions in times of declining real GDP growth rates; hence, they behave procyclically. They also find that there is positive relationship between loan loss provisions and bank earnings, which supports income smoothing hypothesis.

Bikker and Metzemakers (2002) analyze 8000 bank from 29 OECD countries in order to see how banks' loan loss provisioning behavior is related to the business cycle for the period from 1991 to 2001. They find that provisioning turns out to be substantially higher when GDP growth is lower, reflecting increased riskiness of the credit portfolio when the business cycle turns downwards, in other words, loan loss provisioning behaves procyclically.

Kearns (2004) analyzes the impact of the macroeconomic environment on loan loss provisions for Irish credit institutions. The author finds that in Ireland the level of loan losses, proxied by loan loss provisions, rise when GDP growth declines and also when unemployment rises. The author also finds that the coefficient on earnings was significantly positive which supports income smoothing theory.

Craig et al. (2006) run macro panel data depending on the observations of 11 Asia-Pacific countries for the period 1960-2004 and micro panel data depending on the observations of 300 Asian banks for the period 1996-2003. In a nutshell, they investigate the procyclicality in the financial system. They find that housing prices accelerates procyclical credit growth especially due to the changes in collateral values. They also find that increased housing prices and collateral values lowers loans loss provisioning.

In more a recent study, Packer and Zhu (2012) investigate the procyclicality of loan loss of provisions of Asian banks. They analyze the balance sheets of 240 banks in 12 Asian economies during the period 2000–2009 and they find evidence that countercyclical loan loss provisioning has dominant factor throughout emerging Asia economies.

2.4 Concluding Remarks

After the global crisis, as the importance attached to systemic risk increased, macro stress testing exercises have come to the fore in both academic studies and the analyses by supervisory authorities and international institutions in order to thoroughly evaluate the resilience of banking sector under severe but plausible conditions. Taking a glance at the literature, macro stress testing practices are mostly exercised by adopting either a VAR or a panel data modelling approach. However, in order to have a full-fledged stress testing framework, more granular and compact modeling initiatives especially by the central banks have been underway just after the crisis. To achieve this, these studies combine a macro model, mostly a VAR model to be used to construct scenarios, with micro models, which are to be employed to estimate major banking risks, such as credit risk.

On the other hand, existing stress testing studies neglect nonlinear data generating mechanisms although there is a vast literature on explaining the nonlinear characteristic of macroeconomic time series and the studies produced especially after the global crisis have drawn attention to possible nonlinearities inherent in the financial system. Therefore, earlier literature suffers from the unfavorable consequences of building its setup on a strict assumption of linearity and the usefulness of these studies is questionable to some extent.

In a nutshell, this thesis aims to make a contribution to existing macro stress testing literature by considering the nonlinear characteristics of macro and micro time series in both VAR and panel data models. Further, considering its compactness by combining macro and micro models, granularity through evaluating the credit risk based on bank-level data and its focus on the interaction between business and financial cycles, including both first and second round effects, the thesis is also the first study among linear stress testing studies concentrating on Turkish banking sector.

CHAPTER 3

A BRIEF OVERVIEW OF THE TURKISH ECONOMY: 2002-2012

This chapter summarizes the main developments regarding the macroeconomic outlook and how the balance sheet and risk profile of the banking sector have evolved in the analysis period in order to illuminate the economic and financial background of the empirical analyses in the following chapters.

3.1 Macroeconomic Environment

Starting 1980s the economy in Turkey became subjected to fundamental changes with the liberalization efforts. Through IMF-supported structural adjustment programs, Turkey initiated to liberalize its economic and financial systems. The main aims of the structural reforms were to transform the economy toward a more market-oriented structure and control balance of payment imbalances and inflation. Also, from a financial perspective, the reforms targeted to encourage the financing mechanisms alternative to bank credit, such as capital markets, and change the oligopolistic structure in the banking sector (Öniş and Riedel, 1993). On the other hand, during this first wave of reforms in financial markets[1], these reformatory strategies were mostly based on deregulation activities in order to create a competitive environment in the financial markets (Atiyas and Ersel, 2010). In this sense, this approach was flawed due to the fact that it disregarded the necessitated regulatory and supervisory aspects.

At the end of this decade, another significant event, the liberalization of the capital account, took place in 1989. Turkey was among the first countries opening

[1] Atiyas and Ersel (2010) argues that there are two major reformatory agendas towards financial system in Turkey: First one was applied during 1980-1989 period concentrating on liberalization. And the second one was implemented in line with a disinflation program after 1999.

up its financial system and integrated with the global financial markets. Ersel (2013) argues that during the era of reform, years 1981-1991, the reform program in many ways was not completely satisfactory, but the program has achieved its stated objectives. Major outcomes of the reform include: (i) Increased role of the market mechanism, (ii) broadened and deepened financial markets (but the public sector continued to be the main recipient of financial resources due to high public deficits), (iii) high real interest rate due to the financial repression by high public borrowing requirements, (iv) sharp decline in the public sector's manufacturing investments and inadequacy of the private investments to cover this shortfall, (v) high inflation, and (vi) softened foreign exchange constraint (Ersel, 1991).

The liberalization of financial services and capital account led to an increase in public sector deficits through relaxing the public sector borrowing constraints by financing from both domestic and international markets (Ersel, 2013). In 1990s integrated with global financial markets, Turkey started to receive larger international capital inflows. Akyüz (2007) argues that procyclical character of capital inflows often results in procyclical fiscal policy especially in emerging markets. Hence, in addition to the unstable public sector balance, the countercyclical aspect of budgetary policies was eroded. Moreover, Boratav et al. (1996) emphasize the chronic instability in the Turkish economy due to high and fluctuating inflation rates and erratic changes in the current account of balance of payments after the introduction of the liberalization.

In order to eliminate the distress in the economy mainly due to high inflation, unsustainable public debt stock and the fragile financial system, in December 1999, with the support of the IMF, an exchange rate-based stabilization program was put into implementation (Akyüz and Boratav, 2003). However, the program was ended up with a financial crisis in November 2000 with a failure to deliver its main premises to stabilize the economic and financial conditions. In February 2001, the currency peg was abandoned and replaced by a free floating regime.

Following the 2000-2001 financial crises, the rise in interest rates and depreciation of the Turkish lira fueled the increase in production costs and, in turn, inflation, and led to a decrease in domestic demand and industrial production (Figure 1). In order to restore the confidence in the economy and the stability in the markets the “Transition to a Strong Economy Program” was introduced in June 2001 (Undersecretariat of Treasury, 2001). The Program was aimed to achieve disinflation, the reduction of the debt burden and the attainment of sustainable high growth rates (Central Bank of the Republic of Turkey, 2003). It also aimed to restructure the financial system and restore the fiscal discipline for guaranteeing a sustainable budget and public debt policy through a series of macro structural reforms. Accordingly, as it will be discussed in detail, the Banking Re-Structuring Program was announced in May 2001.

The Transition to a Strong Economy Program introduced a new framework for both monetary and foreign exchange policies. In line with this, a floating exchange rate regime was adopted. Also, implicit inflation targeting regime was introduced, implemented until 2006 when Central Bank of Turkey started to announce explicit inflation targets. This regime solely focuses on future inflation and central bank uses short-term interest rates as the main policy instruments to curb inflation (Central Bank of the Republic of Turkey, 2003).

The stabilization program started in 2001 delivered an improvement in the price stability outlook as the inflation decreased consecutively (Figure 2). The fiscal discipline and the monetary policies in line with the inflation target reduced interest rates and caused the Turkish lira to appreciate. Decreased uncertainties and the stable conditions in the financial markets allowed the Turkish economy to enter into a recovery period after the financial crises. The fall in interest rates (Figure 3) and the appreciation of the Turkish lira against fueled the optimistic expectations and preferences for investment and consumption became more attractive under favorable economic environment.

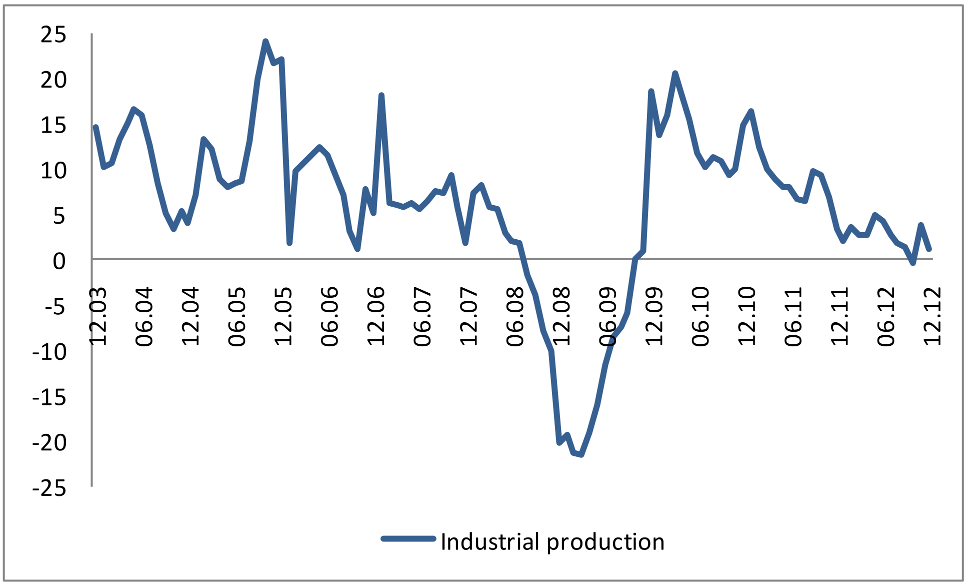

Figure 1: Industrial production (Annual percentage change)

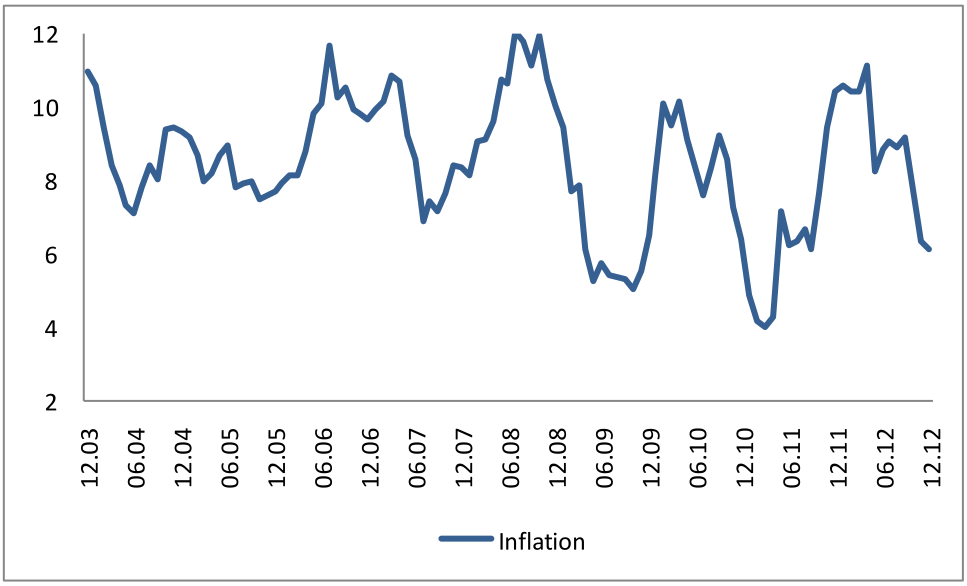

Figure 2: Consumer price index (Annual percentage change)

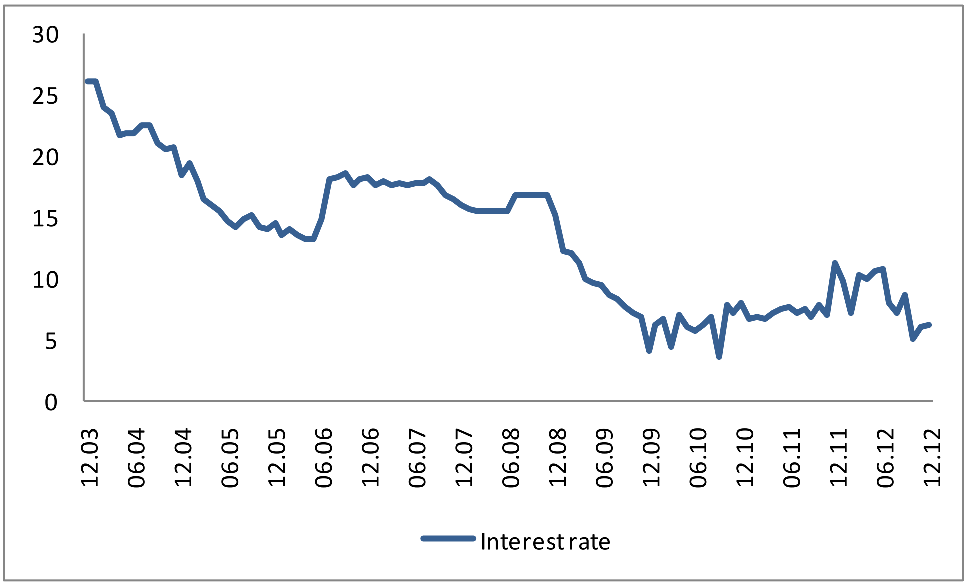

Figure 3: Interbank overnight deposit rates (percent)

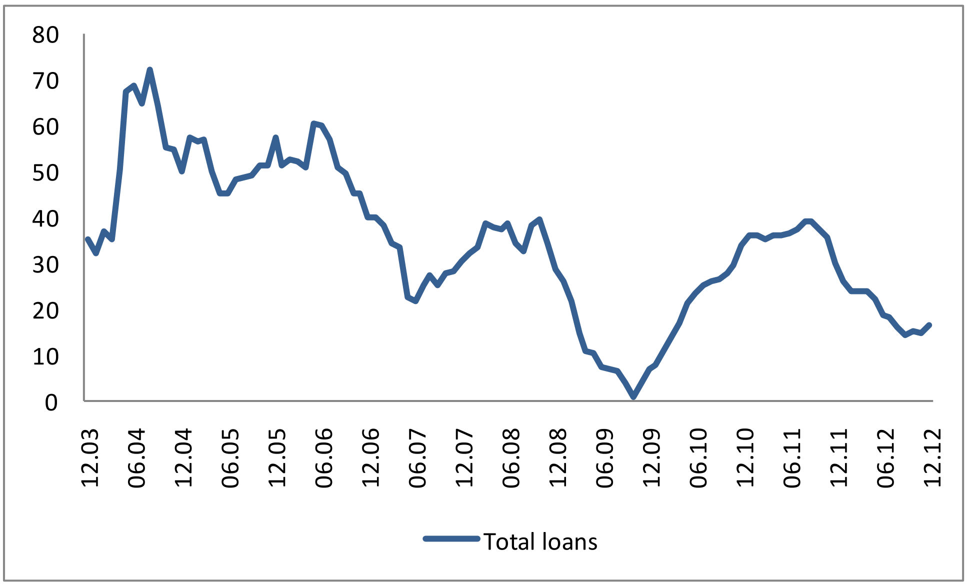

Figure 4: Total loans (Annual percentage change)

With the restoration of the stability in financial markets and decreased macroeconomic uncertainties, the increase in deferred consumption and investment expenditures fed into demand for loans (Figure 4). Although after the 2000-2001 crises domestic credit slumped mainly due to the deterioration in domestic demand and the real income of individuals, the credit demand increased substantially. Also, as banks' portfolio preferences changed and they transformed the composition of asset side of their balance sheets, they started to extend more loans to the private sector rather than the public sector, their intermediary functions developed and hence credit supply increased.

During the period of May-June 2006 turmoil in global financial markets brought about an increase policy interest rate and, in turn, credit interest rates. Outflow of capital from emerging markets led to a hike in risk premia and depreciation of local currencies in these markets. Hence, in Turkey, along with the increase in interest rates, the depreciation of Turkish Lira restrained the domestic demand. The deterioration in inflationary expectations, despite the decrease in the oil prices, resulted in an increase in inflation. Hence, investment expenditures and consumption declined and credit demand shrank. The explicit inflation targeting regime was introduced from 2006 and tight monetary stance due to financial turmoil ended in the third quarter in 2007. Total domestic demand and demand for loans increased.

The financial crisis that started in US financial markets in August 2007 evolved into a global crisis in 2008, which resulted in adverse effects on the real economy in Turkey starting from the second half of 2008 (Central Bank of the Republic of Turkey, 2008a). In parallel to the decline in international interest rates due to sharp contraction global output, interest rates in Turkey dropped significantly. Deterioration in expectations and economic outlook hampered the credit growth and banking sector's total loans declined sharply. However, with the effect of sizeable and front-loaded cuts in policy interest rates and the surge in capital inflows due to more rapid decline in interest rates in advanced economies than domestic interest rates led to surge in total domestic demand, especially in consumer expenditures, and credit demand. Banks also loosened their credit conditions considerably.

As they provide more favorable growth prospects and international funds searched for a higher yield around the globe, emerging markets including Turkey continued to attract massive capital inflows. Hence, since banking sector had the ability to reach ample external funds easily at lower costs, it increased credit supply significantly. In turn, favorable credit conditions paved the way for higher investment and consumption as the expectations improved and trust in financial markets was restored.

On the other hand, as massive capital inflows fed into domestic credit and credit volume rapidly expanded and concerns on financial stability increased significantly. As a result, the Central Bank of Turkey announced its exit strategy from crisis measures in April 2010. Also, it also adopted several measures to limit macrofinancial risks, especially the short term capital flows, excessive appreciation of the exchange rate and excessive credit growth. In this period, it designed a policy mix requiring the joint use of the interest rate corridor between overnight borrowing and lending rates and one week repo rate, the main policy tool. It started to use reserve requirement ratios actively and the remuneration of reserve requirements ended. The Central Bank of Turkey also introduced reserve options mechanism to serve as an automatic stabilizer against capital flows, which allows the banks to hold a certain portion of the Turkish lira reserve requirements in FX and gold. Other authorities, including Banking Regulation and Supervision Agency, introduced macroprudential measures to reduce risks related to financial stability.

In the last quarter of 2011, the credit growth rate began to lose pace. Also in this period, due to the sovereign debt problems in the Euro Area and the deterioration in global growth outlook the tension in the global financial markets increased considerably. This development interrupted the normalization of process in the policy interest rate abroad that started in second half of 2010. In Turkey, on the other hand, Central Bank of Turkey explicitly highlighted the increasing role of financial stability and concentrated its efforts to contain macro financial risks.

3.2 Financial Environment

After the 2000-2001 crises, in order to restore the confidence and stability, and to create a framework for restructuring the public administration and economy, Transition to a Strong Economy Program was introduced in June 2001 (Undersecretariat of Treasury, 2001). Within the framework of the Program, a series of macro structural reforms were put into implementation. Restructuring the financial system and restoring the fiscal discipline were among major reform targets. The measures and policies that were implemented in line with the Program delivered the reduced public sector deficit and remove the pressure of high public borrowing requirements on financial markets.

Also, in May 2001 Banking Re-Structuring Program was announced (Banking Regulation and Supervision Agency, 2001). The Program aimed to recover the deterioration caused by the 2000-2001 crises in the banking sector and strengthen the sector by resolving the weak banks (Banking Regulation and Supervision Agency, 2010). The strategy under this program rested on four main pillars: the financial and operational restructuring of state banks, the resolution of the Savings Deposit Insurance Fund banks, the strengthening of private banking; and, the strengthening of the legal and regulatory environment (Banking Regulation and Supervision Agency, 2001).

The fundamental and comprehensive restructuring measures enabled the banking sector to return its intermediary functions (such as granting loans to real sector), and enhanced its strength against external shocks and upgrade its capacity towards sound risk management. The sound functioning of the financial system in performing its intermediation activities have great significance for price stability (Central Bank of the Republic of Turkey, 2006a).

During the analysis period, as it is seen from Figure 5, it is possible to observe a fundamental change in asset structure of the banking sector. The gradual increase of economic stability and positive expectations all contributed to the change in the composition of assets by the banking sector (Central Bank of the Republic of Turkey, 2005). With the return of banks to their intermediation activities, the share of loans to private sector surged substantially. The effectiveness of the credit channel in the monetary policy transmission mechanism, functioning through the financial system increased (Central Bank of the Republic of Turkey, 2006a). Currently, loans explain the 58 percent of banking sector assets.

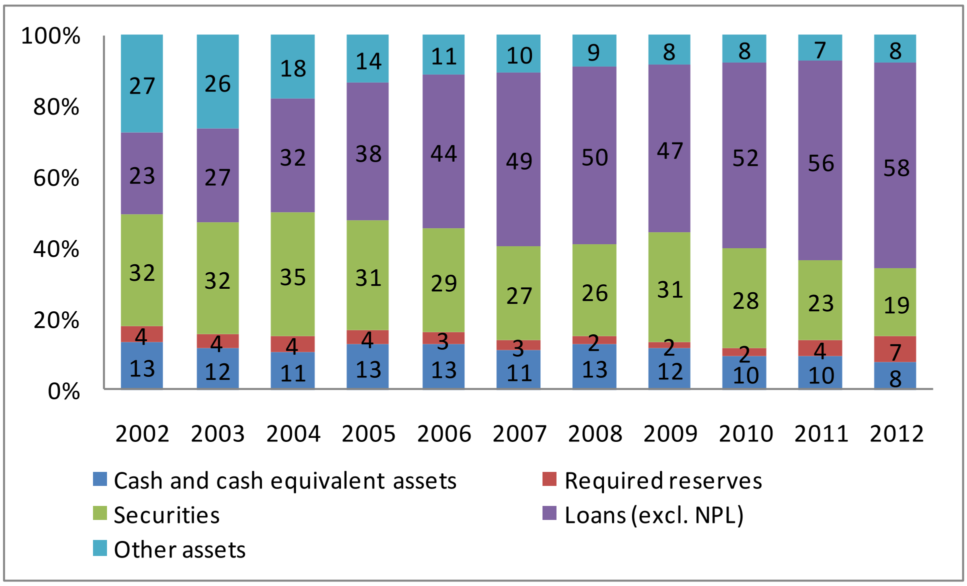

Figure 5: Asset structure of the banking sector (%)

Securities portfolio, particularly the share of government securities, declined considerably during the analysis period. The main rationale behind this development is the decline in fiscal dominance of public sector and so in the supply of government securities. On the other hand, the initial increase at the beginning of the period mainly due to the transfer of domestic debt securities especially to state banks to cover their losses.

Although there is a change in the liability structure of the banking sector with the rapid credit expansion (Figure 6), loans continued to be funded with stable resources and they mainly consist of deposits. Deposits are in general more stable funds than non-deposit resources (Central Bank of the Republic of Turkey, 2005). On the other hand, in 2012 loan to deposits ratio exceeded 100 percent level for the first time, indicating increased liquidity risk. This development also indicates that banks finance their credit operations by resources other than deposits and own funds.

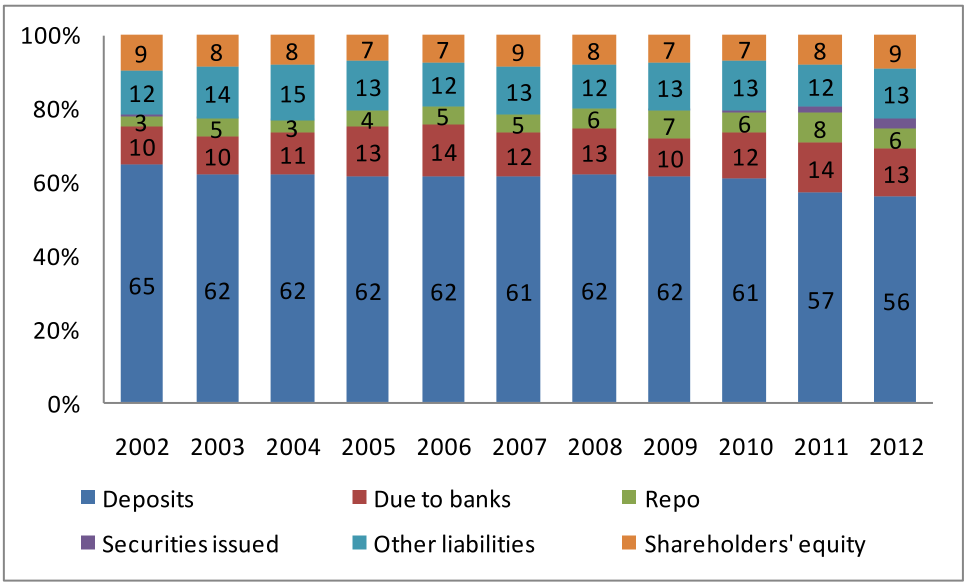

Figure 6: Liability structure of the banking sector

Indeed, during this period we witness a substantial hike in capital inflows to emerging countries, which enables banks to reach external funds at lower costs and to finance their credit operations more comfortably. Another significant development is that in 2010 Banking Regulation and Supervision Agency allowed banks to issue bills and bonds in the domestic market as well as abroad. Hence, the share of securities issued in total liabilities increased to some extent.

Credit volume, which had an obviously decreasing trend especially after the crises experienced during 2000 and 2001, started to rise starting from the third quarter of 2003 and not only its share in the GDP but also its share in total assets began to follow an increasing trend (Figure 7). The macroeconomic stability and positive expectations were among the main factors paving the way for increasing trend of credit. The increase in deferred consumption and investment expenditures fed into demand for loans. The increase in consumer loans and credit cards, i.e. retail loans, fueled the growth in total loans as banks attached more importance to the private banking services (Central Bank of the Republic of Turkey, 2005).

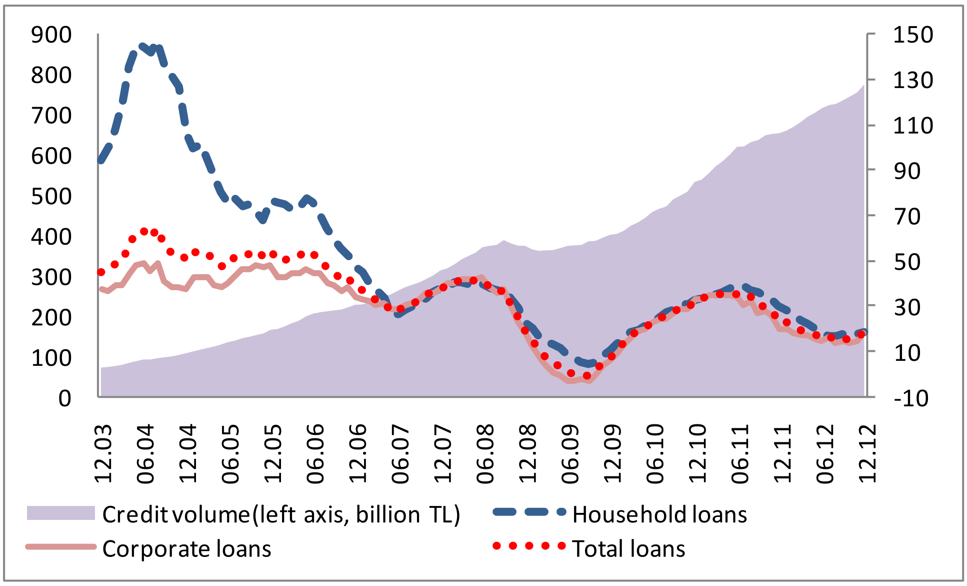

Figure 7: Banking sector loans (annual percentage change, billion TL)

Due to the May-June 2006 fluctuation in financial markets, the increase in credit interest rates led to a decline in retail loans, which is the main driver of the growth of the credit volume (Central Bank of the Republic of Turkey, 2006b).

After the global crisis of 2008, another major contraction occurred in the credit volume (Figure 7). The crisis in the global markets and the concerns on the high default rates increased cost of international funds for banks and this, in turn, reduced the credit supply of the banking sector. Within the same period we observe a decline in demand for loans due to the contracted economic activity (Central Bank of the Republic of Turkey, 2008b). The slowdown in credit expansion was resulted mostly from the decrease in loans by foreign and private banks.

The growth rate of corporate loans is the one most affected from the tighter credit conditions and a slowdown in economic activity. In order to lessen the financial challenges that small and medium sized companies have faced due to the tight lending terms, Credit Guarantee Fund[2], a non-profit incorporated company established in 1991, was reregulated in order to facilitate credit usage in investment and financing of small and medium size enterprises through providing them guarantee.

The measures taken by the Central Bank of Turkey to curb the effects of the global financial crisis fueled the recovery in economic activity. The improved risk perceptions of banks and the low course of loan interest rates enabled the maintenance of a gradual recovery in the credit growth rate since the last quarter of 2009 (Central Bank of the Republic of Turkey, 2010). In sum, all types of loans increased as a result of the recovery in economic activity and low interest rates.

The rise in credit volume and current account deficit, along with acceleration of short-term capital inflows has brought into the agenda the risks regarding financial stability. By implementing the new policy mix, Central Bank of Turkey aimed to bring credit growth to reasonable levels for financial stability and to extend maturities of portfolio investments (Central Bank of the Republic of Turkey, 2011). Also Banking Regulation and Supervision Agency introduced macroprudential measures[3] to reduce risks related to financial stability. Hence, the credit growth rate has started to lose its pace starting from the second half of 2011.

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[2] For more information please refer to Box 10 in Central Bank of the Republic of Turkey (2009) and Box 13 Central Bank of the Republic of Turkey (2010).

[3] For example, Banking Regulation and Supervision Agency stipulated that banks with a ratio of consumer loans to total loans above 20 percent and banks with a ratio of non-performing loans in

In sum, the policy mix implemented by Central Bank of Turkey and measures taken by Banking Regulation and Supervision Agency, the credit growth rate lost its pace considerably.

The capital adequacy ratio, the own funds divided by the risk weighted assets, measures the resilience of banks against potential adverse shocks and the profitability indicators signal the banks' financial health. It is evident from Figure 8 that the capital adequacy ratio hovered above the minimum legal requirement of 8 percent and the target ratio of 12 percent for all the periods under review.

As the banks return their main intermediation activities and restructure their balance sheets towards granting more credit to households and corporates, which is a riskier business than providing funds to public sector through government securities, its risk weighted assets increased at a higher rate relative to capital. As a result, although it is still above the minimum legal requirement and target ratio, the capital adequacy ratio declined constantly due to the faster growth of risk-weighted assets compared to own funds. The capital adequacy ratio, which was about 30 percent at the end of 2003, dropped to almost 18 percent at the end of 2012.

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other consumer loans to total other consumer loans above 8 percent, should set aside 4 percent general provision for other consumer loans that fall within Group 1 (loans with standard qualifications and other receivables) and 8 percent general provision for Group 2 (Loans and other receivables that are closely monitored) for other consumer loans that they will extend as of 18 June 2011. Other consumer loans comprise all consumer loans other than housing and vehicle loans. For more information please check Box III.3 in Central Bank of the Republic of Turkey, 2011.

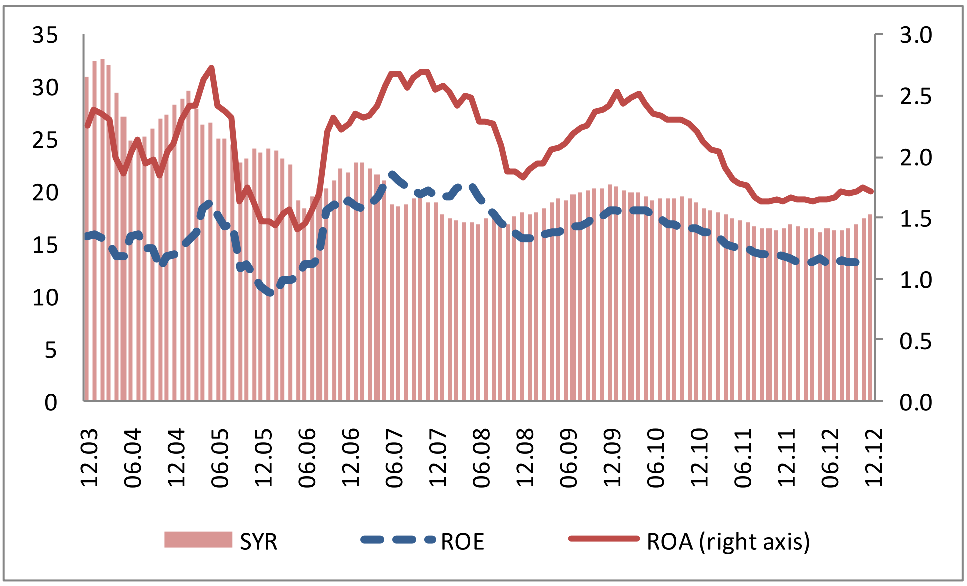


Figure 8: Capital adequacy ratio (CAR), return on equity (ROE) and return on assets (ROA) (%)

In a decreasing interest rate environment, banking sector managed to maintain its profitability by focusing on sustainable income sources and operational efficiency (Central Bank of the Republic of Turkey, 2005). Bank profitability remained mostly stable during the periods under review and provided sufficient cushion against external shocks. Analyzing the development of profitability indicators, namely return on assets and return on equity, the adverse effects of nonperforming loans, which are high but in decreasing trend, on banks profitability performance are still felt. For example, the profitability performance of the banking sector deteriorated due to the losses declared by private banks as a result of high provisions set aside. At the end of 2008, banks' preference to keep sufficient liquidity and surge in nonperforming loans led to a decline in the profitability indicators.

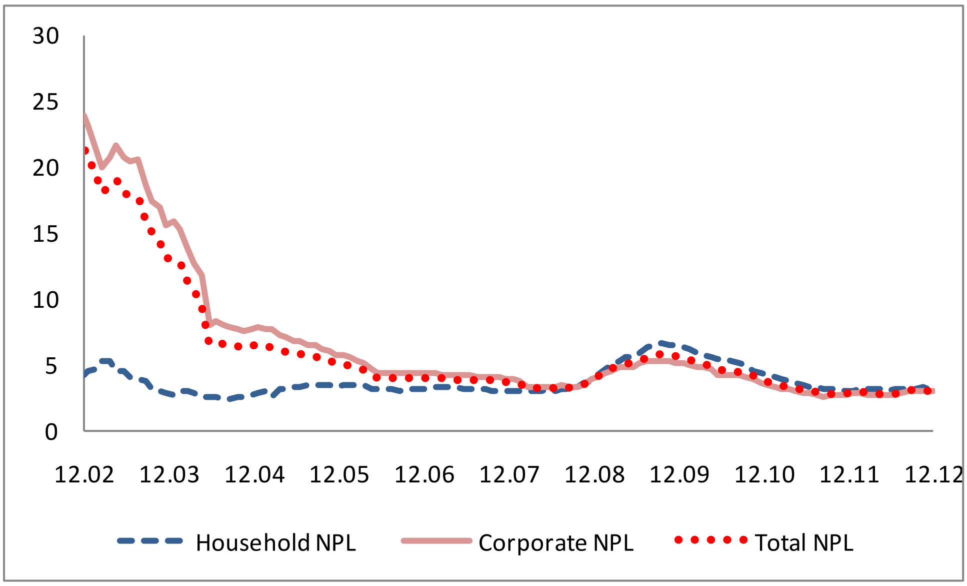
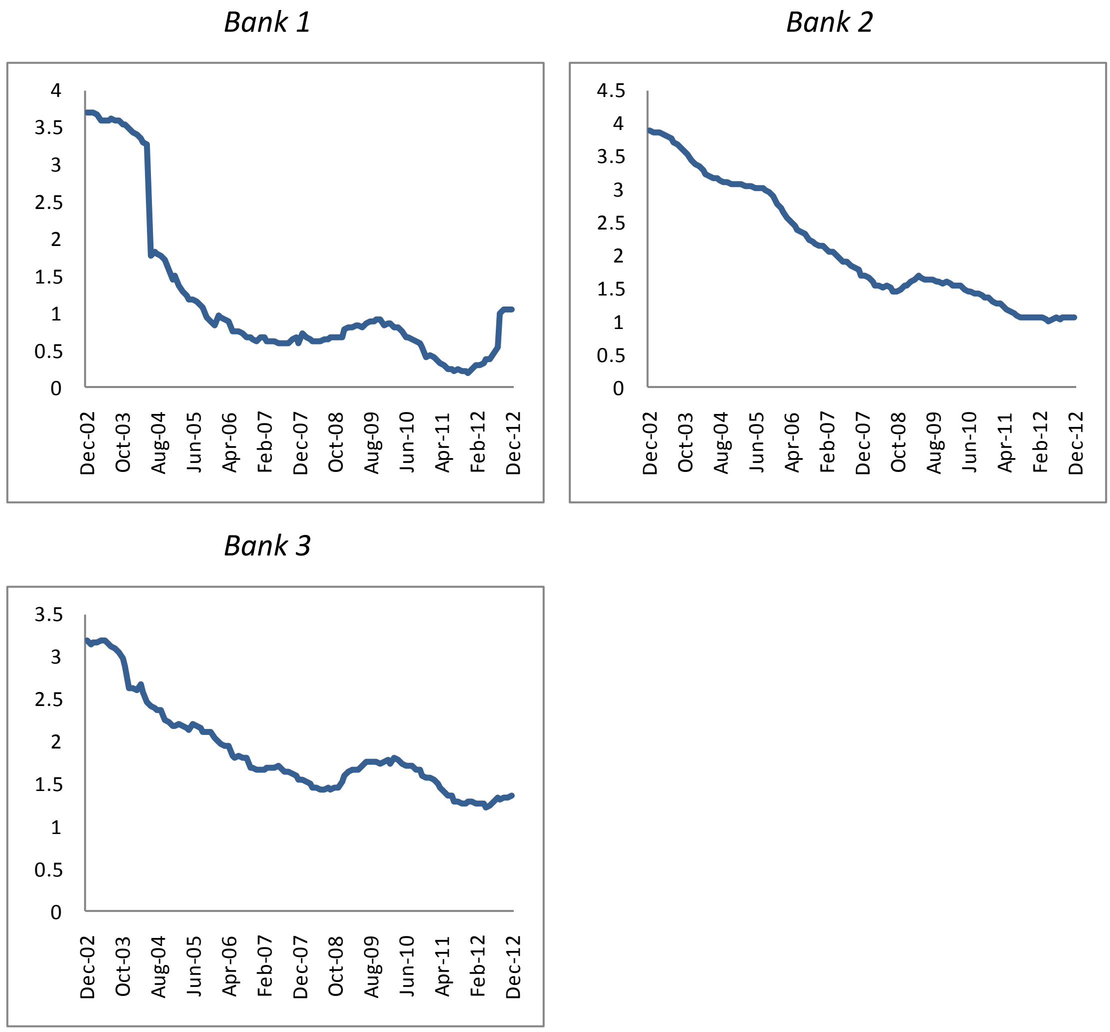


Figure 9: Nonperforming loan ratio of the banking sector (%)

Under stable macroeconomic conditions, during the periods under review nonperforming loan ratio has followed a descending trend (Figure 9). The improvement in the debt payment capacity of the corporate sector and households positively contributed to this trend. Another important factor playing a role in this trend is restructuring the loans of firms under the "Istanbul Approach[4]" which was put into implementation after the 2000-2001 crises.

[4] In order to rehabilitate the firms that became insolvent due to the 2000-2001 crises, Law No:4 743 dated 31.01.2002 on "Restructuring of Debts to the Financial Sector and Amendments to be made to some Acts" was issued. The firms facing temporary liquidity problems and being capable of continuing their activities were assessed and their loans were restructured. For more information please refer to the Box II.2.1.1.2.2 in Central Bank of the Republic of Turkey, 2005.

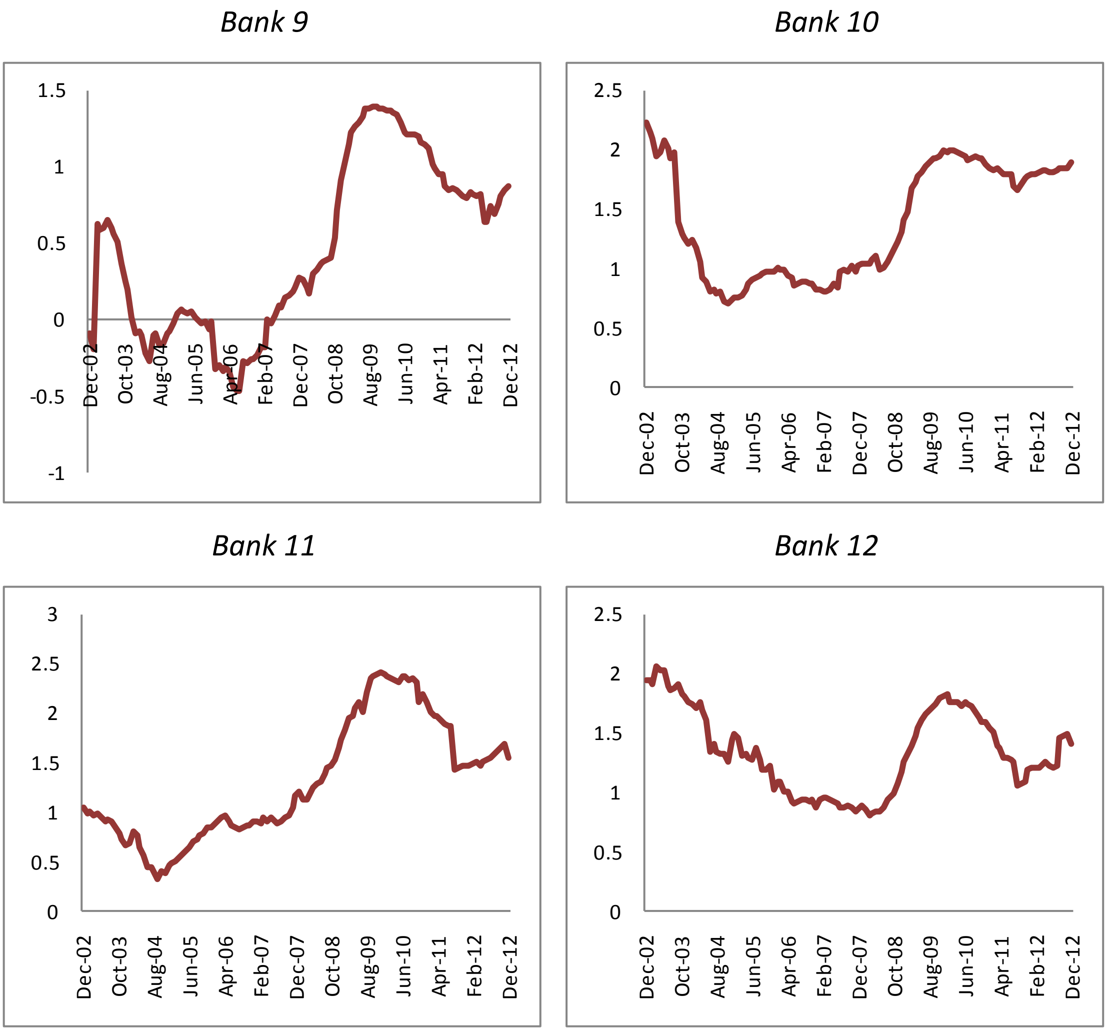


a. Public banks

Figure 10: Development of nonperforming loan ratio (in log value) by banks

b. Private banks

Figure 10: Development of nonperforming loan ratio (in log value) by banks (cont'd)



c. Foreign banks

Figure 10: Development of nonperforming loan ratio (in log value) by banks (cont'd)

The development of the nonperforming loans over time by banks is given in Figure 10. After 2000-2001 crises, banks are back to main financial intermediation activities. In parallel to the strong credit growth, there is a sharp decline in the ratio of nonperforming loans to total loans. Evaluating the decline in the level of the nonperforming loans, it can be said that the decline in the ratio is not only from the credit growth but also from the improved asset quality of banks.

During the rapid credit growth period, however, the nonperforming loans started to increase from the year 2005 as banks started to extend loans to riskier customers. Although this is not obvious from Figure 9 where the ratio of nonperforming loans to total loans plotted, this development can be observable from Figure 10 because of the differences across banks. Comparing across bank groups based on the type of ownership, this finding is more valid for private banks and, to some extent, for foreign banks. The financial turmoil in May-June fluctuation worsened the deterioration in the nonperforming loans especially for foreign banks due to the tight financial conditions and the unfavorable economic outlook.

With the global crisis in 2008, deterioration in expectations and economic outlook hampered the credit demand growth and banking sector's total loans declined sharply. Decrease in economic growth and, in turn, impairment in the profit ratios of firms and the income of individuals worsened the quality of banks' credit portfolio and led to a jump in nonperforming loans. The extraordinary measures that taken abroad and in Turkey to curb the adverse effects of the global crisis restored the confidence in local financial markets and domestic growth prospects. The deterioration in the nonperforming loans stopped and the asset quality of the banking sector improved. Although the nonperforming loans levels decreased to its pre-crisis levels, for some foreign banks current level is still higher than the pre-crisis levels.

CHAPTER 4

ECONOMETRIC MODELS AND METHODOLOGY

4.1 Introduction

After the global crisis, it has become obvious that evaluating the risk profile of the banking sector necessitates a more full-fledged stress testing approach. One practical way of doing this is to adopt an augmented approach, which combines separate models concentrating on specific risk components such as credit risk, market risk, liquidity risk etc. A macroeconomic model, mostly a VAR model, completes this set of models by examining the interaction between financial system and real economy in order to produce severe but plausible scenarios.

In line with these recent modeling efforts for macro stress testing, this thesis proposes a suite of models, which are a set of independent but complementary models. The proposed approach concentrates primarily on the credit risk of the banking sector, which the major risk category. In order to compose macro stress testing framework, first it is necessary to link financial stability to macroeconomic stability and estimates the relationship between macroeconomic variables and macrofinancial variables. Second it is essential to employ a panel data techniques to uncover the role of these macroeconomic and macrofinancial variables in exploring the dynamics of nonperforming loans.

Therefore, we first examine the relationship among macroeconomic and macrofinancial variables in order to reveal the interaction between the real sector and the financial system. First, we construct a linear VAR model. Then, considering the possible nonlinearities (Neftçi, 1984; Hamilton, 1989; Sichel, 1993; Terasvirta and Anderson, 1992; Öcal and Osborne, 2000; Huang et al, 2011) that may be inherited in the macroeconomic and macrofinancial series, a nonlinear model is considered.

Next, in order to find the determinants of the asset quality of the banking sector, we employ panel data models. These models cover a range of models depending on whether it is static or not and whether it is linear or nonlinear. Hence, we start with static panel data models, i.e. fixed and random effects panel data models. In order to measure the persistency in nonperforming loans, a dynamic panel data model is also considered. Then, with a view to the nonlinearity in the financial systems, a nonlinear panel data model is taken into consideration.

VAR model is mainly used to construct macro scenarios which represent external shocks for the financial system. Then, it is possible to measure the stress on nonperforming loans, a measure for credit risk, due to external shocks to the financial system.

The plan of this chapter is as follows. Section 4.2 presents a linear and a nonlinear VAR models. In Section 4.3, several panel data models are reviewed within the context of this thesis. Section 4.4 discusses forecasting and stress testing issues. Section 4.3 concludes the chapter.

4.2 VAR Models

4.2.1 Linear VAR Model

A VAR framework provides a proper way to analyze the dynamic interactions between macroeconomic and macro financial variables such as banking sector's total loans. A VAR model is a multivariate generalization of the single equation autoregressive model and is first introduced by Sims (1980) in order to analyze macroeconomic relationships.

A possible modeling scheme for a VAR model roughly suggests basic elements below:

(i) Choosing appropriate variables by using economic intuition in line with econometric theory.

(ii) To ensure the stationarity of variables, unit root tests should be employed.

(iii) Determining the order of VAR model by appropriate information criteria such as AIC, SIC and log likelihood ratio test.

(iv) Checking possible structural breaks and outliers in data in order to decide deterministic components to be included in the model.

A VAR model captures the dynamic interactions between endogenous variables of interest. Let y_t be a (nx1) vector series at time t, $y_t=(y_{1t}, \ldots, y_{nt})$. A p^{th} order VAR model of y_t is a linear dynamic of the following form:

$$y_t = c + \sum_{i=1}^{p} \theta_i y_{t-i} + v_t \qquad \textbf{(4.1)}$$

where θ_i is a (nxn) matrix of coefficients for i=1,2,…,p. c represents the drift or deterministic term. The vector $v_t=(v_1, \ldots, v_t)$ is an unobservable error term that follows multivariate white noise process. That is, the v_t is an independent stochastic vector with $E(v_t v_{t+s})=0$ for every $s \neq 0$ and $E(v_t v_t')=\Omega$ with Ω an (nxn) symmetric positive definite matrix, which is variance-covariance matrix of v_t.

As an alternative representation for Equation 4.1, the notation of multivariate linear regression model can be used, which has a more compact form (Lutkepohl, 2005).

$$Y = BX + V \qquad \textbf{(4.2)}$$

where $Y=(y_1, \ldots, y_T)$ is a (nxT) matrix, $B=(c, \theta_1, \ldots, \theta_p)$ is a (nx(np+1)) matrix, $V=(v_1, \ldots, v_T)$ is a a (nxT) matrix, $X=(X_1, \ldots, X_T)$ is a a ((np+1)xT) matrix and $X_t = \begin{bmatrix} 1 \\ y_{t-1} \\ \vdots \\ y_{t-p} \end{bmatrix}$ is a ((np+1)x1) vector .

V is independent and identically distributed with mean zero and variance-covariance matrix Σ. The log likelihood function can be defined as (Hamilton, 1994):

$$\mathcal{L} = -\frac{Tn}{2}(log2\pi) - \frac{T}{2}log|\Sigma^{-1}| - \frac{1}{2}\sum_{t=1}^{T}(y_t - BX_t)'\Sigma^{-1}(y_t - BX_t) \quad \textbf{(4.3)}$$

where y_t is a typical row of Y.

Then the maximum likelihood estimator of B can be given as (Hamilton, 1994):

$$\hat{B} = [\sum_{t=1}^{T} y_t X_t][\sum_{t=1}^{T} X_t X_t']^{-1} \quad \textbf{(4.4)}$$

If B-hat denotes the matrix of OLS estimates, then the maximized value of the log likelihood function is:

$$\mathcal{L} = -\frac{Tn}{2}(log2\pi) - \frac{T}{2}log|\Sigma^{-1}| - \frac{1}{2}\sum_{t=1}^{T}\left(y_t - \hat{B}X_t\right)'\Sigma^{-1}\left(y_t - \hat{B}X_t\right) \quad \textbf{(4.5)}$$

Then the maximum likelihood estimator of Σ can be given as

$$\hat{\Sigma} = \frac{1}{T}\sum_{t=1}^{T} \hat{v}_t{}'\hat{v}_t \quad \textbf{(4.6)}$$

In a VAR model, the stationarity of the variables should be ensured. In this context, the y_t is stable if all eigenvalues of θ, which is shown below, have modulus less than 1.

$$\theta = \begin{bmatrix} \theta_1 & \theta_2 & \cdots & \theta_{p-1} & \theta_p \\ I_n & \cdots & \cdots & 0 & 0 \\ 0 & I_n & \cdots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \cdots & I_n & 0 \end{bmatrix} \quad \textbf{(4.7)}$$

In order to reveal whether the series are stationary or non-stationary, augmented Dickey-Fuller (ADF), Philips-Perron (PP) and Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) tests can be used. If the series are found to be nonstationary, one remedy is to take the first difference of the series.

ADF test is used to determine whether H_0: α=0 (nonstationarity) against H_1:α<0 (stationarity). Consider the following model:

$$\Delta y_t = \alpha y_{t-1} + \beta_1 \Delta y_{t-1} + \cdots + \beta_p \Delta y_{t-p} + v_t \qquad \textbf{(4.8)}$$

And the relevant t ratio is

$$t_{\hat{\alpha}} = \hat{\alpha}/s.e.(\hat{\alpha}) \qquad \textbf{(4.9)}$$

On the other hand, PP test estimates an ordinary Dickey Fuller equation and instead employs a modified t ratio in order to test H_0: α=0 against H_1: α<0. Hence it estimates the following model:

$$\Delta y_t = \alpha y_{t-1} + v_t \qquad (4\textbf{.10})$$

The relevant t ratio is

$$\bar{t}_\alpha = t_\alpha(\gamma_0/f_0)^{1/2} - T(f_0 - \gamma_0)s.e.(\hat{\alpha})/2{f_0}^{1/2}s \qquad \textbf{(4.11)}$$

where s is the standard error of disturbances, γ_0 is a consistent estimate of the error variance and f_0 is the Newey-West long-run variance of disturbances.

Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) propose an alternative test where the null hypothesis is stationarity. In KPSS, the basic idea is to decompose a time series into the time trend, a random walk and a stationary error term (Verbeek, 2004). The KPSS test statistic is given as:

$$LM_{KPSS} = \sum_{t=1}^{T} S_t^2/\hat{\sigma}^2 \qquad \textbf{(4.12)}$$

where $S_t = \sum_{s=1}^{t} v_s$ for all t, v_t is the residuals from regression of the series y_t on an intercept and a time trend t and $\hat{\sigma}^2$ is the variance of the residuals.

It is imperative to determine the order of VAR model. Multivariate information criteria or log likelihood ratio (LR) test can be employed in order to determine the lag length.

The LR test statistic is as follows:

$$LR=(T-c)\{\log(|\Sigma_r|) - \log(|\Sigma_u|)\} \quad \textbf{(4.13)}$$

where T is the number of total observations and c is the number of variables in unrestricted equation. Σ denotes variance-covariance matrix of residuals. r and u denote restricted and unrestricted VAR models. Rejection of the null of equality indicates that the unrestricted VAR model is recommended.

In addition to the LR test, multivariate versions of the information criteria can be used. Akaike information criterion is defined as:

$$MAIC = T \log(\Sigma) + 2N \quad \textbf{(4.14)}$$

The Schwarz information criterion is defined as:

$$MSBIC = T \log(\Sigma) + N \log(T) \quad \textbf{(4.15)}$$

Hannan-Quinn information criterion is defined as:

$$MHQIC = T \log(\Sigma) + 2N \log(\log(T)) \quad \textbf{(4.16)}$$

N is the total number of parameters estimated in all VAR equations, which equal to np^2+n. The values of the information criteria are constructed for up to p lags and the number minimizing the value of the given the information criteria provide us the chosen number of lags.

One major inference tool of a VAR model is variance decompositions. Variance decompositions explain the share of the changes in the variables due to their own shocks and shocks to other variables in the system. In this sense, variance decompositions show portion of s step ahead forecast error variance of a particular variable due to the innovations in each explanatory variable.

If the system is stable, for the VAR model in Equation 4.1 its Wold moving average representation can be used as follows:

$$y_t = c + \Psi(L)v_t = c + v_t + \Psi_1 v_{t-1} + \Psi_2 v_{t-2} + \cdots \quad \textbf{(4.17)}$$

In order to define forecast error variance, we can start from this point. The s step ahead forecast can be defined as:

$$E_t y_{t+s} = c + \sum_{i=0}^{\infty} \Psi_i v_{t+s-i} \quad \textbf{(4.18)}$$

Since the forecast error can be defined as the difference between the expected value and the real value, the s step ahead forecast error for the series y_t can be defined as follow:

$$y_{t+s} - E_t y_{t+s} = \sum_{i=0}^{s-1} \Psi_i v_{t+s-i} \quad \textbf{(4.19)}$$

And the mean square error is:

$$(y_{t+s} - E_t y_{t+s})^2 = \sigma_y^2 \sum_{i=0}^{s-1} (\Psi_i)^2 \quad \textbf{(4.20)}$$

where the sigma square is the variance of y_{t+s}.

4.2.2 Nonlinear VAR Model

As it is discussed before, macro time series may show nonlinear characteristics. In order to capture these nonlinear data generating mechanisms, this section specifically focuses on threshold VAR (TVAR) models. Threshold VAR modeling requires to determine certain parameters before the estimation process. In a nonlinear model, transition variable should be determined as well as the order of model should be specified as in a linear VAR model. In such a modeling scheme, it is beneficial to first establish the best linear VAR model. Next, transition variable should be decided. Transition variable could be any variable that is employed in the TVAR model. It is possible to determine transition variable by applying one of the nonlinearity test procedures. Accordingly, choosing the most significant test statistic gives the best candidate for transition variable. After the determination of the transition variable, nonlinear estimation procedure boils down to linear estimation procedure. After estimating the model for all possible values of transition variable, the model with the smallest SSR will give the optimal threshold value.

In order to analyze the effect of credit cycles on macroeconomic stability under different credit regimes, we adopt the approach that is introduced by Tsay (1998). Tsay's method is a generalized version of Chan (1993) and Hansen (1996a) for the univariate case. This approach allows us to check both TVAR type nonlinearities which allows to apply a piecewise linear process and detect threshold values.

A TVAR model is simple extension of a threshold autoregressive model. The TVAR model is specified as follows:

$$y_t = c_j + \sum_{i=1}^{p} \theta_i^{(j)} y_{t-i} + v_t^{(j)}$$
$$if\ r_{j-1} < z_{t-d} \leq r_j \qquad j = 1, \dots, s \qquad \textbf{(4.21)}$$

y_t follows a multivariate threshold model with transition variable z_t and delay parameter d. p denotes the order of the VAR model. Let $-\infty=r_0<r_1<\ldots<r_{s-1}<r_s=\infty$. The transition variable z_{t-d} defines the regimes that TVAR model have. It is also assumed to be stationary and have a continuous distribution. The model has s regimes j=1,…,s and is a piecewise linear model in the threshold space z_{t-d}, but it is nonlinear in time when s>1 (Tsay, 1998). In this nonlinear model, we assume that p is the same for each variable and regime and that the transition variable is the same for each equation (Galvao, 2003). Hence we can estimate each equation separately by ordinary least squares (OLS).

Specifically a two regime TVAR model can be given as under the assumption of i.i.d. error terms:

$$y_t = I[z_{t-d} \geq r]\left(c_1 + \textstyle\sum_{i=1}^{p} \theta_{i1} y_{t-i}\right) + I[z_{t-d} < r]\left(c_2 + \textstyle\sum_{i=1}^{p} \theta_{i2} y_{t-i}\right) + v_t \qquad \textbf{(4.22)}$$

where I[.] is an indicator function which takes the value 1 if the transition variable z_{t-d} is equal or bigger than the threshold value r and zero otherwise.

Tsay's method mainly depends on an arranged regression analysis. As in the linear model, the model building procedure starts with determining the order of the model. After choosing the order of the VAR model by Akaike information criterion, the nonlinearity test is employed. By the nonlinearity test, one can choose the best transition variable. In order to conduct the test statistic, recursive least squares are applied to arranged regression, which yields predictive residuals. By using standardized predictive residuals, nonlinearity, namely C(d), test statistic can be constructed.

As it is known, residuals of a correctly specified linear model are independent under the null hypothesis of linearity. Then any possible correlation between residuals indicates the inadequacy of the model, and hence violation of the linearity assumption, which constitutes the major idea behind nonlinearity tests. Therefore, in detecting nonlinearity there may not be a single test that dominates the others (Tsay, 2010).

Consider the null hypothesis that y_t is linear whereas the alternative hypothesis is that it follows multivariate threshold vector autoregression model. In order to detect the threshold nonlinearity of y_t given that p and d are known, consider the regression below:

$$y'_t = X'_t\Phi + v'_t \quad t=h+1, \ldots, n \qquad \textbf{(4.23)}$$

where h=max(p, d) and $X_t = (1, y'_{t-1}, \ldots, y'_{t-p})'$

Here Φ denotes the parameter matrix. After rearranging the data through ordering the variable z_{t-d} from the smallest to the biggest values, transition variable z_{t-d} assumes values in $S=\{z_{h+1-d}, \ldots, z_{n-d}\}$. Then the arranged regression based on the increasing order of the transition variable z_{t-d} is:

$$y'_{t(i)+d} = X'_{t(i)+d}\Phi + v'_{t(i)+d} \quad i = 1, \ldots, n-h \qquad \textbf{(4.24)}$$

The recursive least squares estimator of the above arranged regression is consistent and so the predictive residuals are white noise if the above arranged regression is linear. In that case, the predictive residuals are uncorrelated with the explanatory variables. Otherwise, there is a threshold model and the predictive residuals are not white noise and ordinary least square estimation is biased. Hence after running a recursive ordinary least squares on the above equation, the following predictive and standardized predictive residuals can be obtained respectively:

$$\hat{v}_{t(m+1)+d} = y_{t(m+1)+d} - \widehat{\Phi}'_{\mathrm{m}} \mathrm{X}_{t(m+1)+d} \qquad \textbf{(4.25)}$$

and

$$\hat{\eta}_{t(m+1)+d} = \frac{\hat{v}_{t(m+1)+d}}{[\ 1+\mathrm{X}'_{t(m+1)+d} V_m \mathrm{X}_{t(m+1)+d}\ ]^{1/2}} \qquad \textbf{(4.26)}$$

where the variance covariance matrix $V_m = [\sum_{i=1}^{m} X_{t(i)+d} X'_{t(i)+d}]^{-1}$

After obtaining standardized predictive residuals, it is possible to run regression of these residuals on the same regressors:

$$\hat{\eta}'_{t(l)+d} = X'_{t(l)+d}\Psi + w'_{t(l)+d} \qquad l=m_0+1, \ldots, n-h \qquad \textbf{(4.27)}$$

where m_0 denotes the starting point of the recursive least squares estimation. To test the linearity of y_t amounts to test that H_0: $\Psi=0$. Then consider the following test statistic:

$$C(d) = [n-h-m_0-(kp+vq+1)]\mathrm{x}\{\ln[\det(S_0)]- [\det(S_1)]\} \qquad \textbf{(4.28)}$$

where $S_0 = \frac{1}{n-h-m_0} \sum_{l=m_0+1}^{n-h} \hat{\eta}_{t(l)+d}\, \hat{\eta}'_{t(l)+d}$

and $S_1 = \frac{1}{n-h-m_0} \sum_{l=m_0+1}^{n-h} \widehat{w}_{t(l)+d}\, \widehat{w}'_{t(l)+d}$

C(d) has an asymptotical chi-square distribution with k(pk+qv+1) degrees of freedom. We reject the null hypothesis that y_t is linear if C(d) is statistically significant.

In the thesis, we follow the procedure below:

1. Find the order (p) of the VAR model.

2. Possible delay parameters could be between 1 and p, $1 \leq d \leq p$.

3. Assuming that d is known, arrange the data. For example, supposing that z_{t-d} is the transition variable, order z_{t-d} ascendingly and other variables in the model accordingly. This procedure is called arranged autoregression.

4. Apply recursive estimation starting with the first m observations. Then update estimation by adding one observation and continue to do this until all observations are used up.

5. Obtain recursive residuals and predictive residuals.

6. Then, carry out the regression in Equation 4.27.

7. If there is nonlinearity, predictive residuals will not be orthogonal to the regressors and null hypothesis H_0 will be rejected.

8. Carry out this procedure for all possible values of d.

9. If null hypothesis is rejected for more than one values of d, choose the one with the strongest rejection as your delay parameter.

10. With this delay parameter, estimate Equation 4.22 for all possible values after deleting first and last 10 percent of the observations. This is necessary to prevent outliers from affecting threshold value.

11. Choose the model with the smallest SSR, which gives the optimal threshold value.

12. Estimate the model with this optimal threshold value.

13. The estimated VAR model is used to forecast the values of industrial production, consumer price index, interbank overnight deposit rate and total loans of the banking sector for the period from 2012:01 to 2012:12.

14. Estimate the panel data model up to 2011:12, which is discussed in the following subsection, and obtain the estimated elasticities. Then, using these elasticities and the one step ahead forecasts from the VAR model, estimate nonperforming loans for the period from 2012:01 to 2012:12.

To sum up, linear and nonlinear VAR models are essentially used to obtain forecasted values for macroeconomic and macrofinancial variables. After the forecasted values derived from the VAR models, they are employed in linear and nonlinear panel data models in order to evaluate the resilience of the banking sector to external shocks.

4.3 Panel Data Models

4.3.1 Linear Panel Data Models

Panel data refers to a compiling of observations on a cross section of, let's say, individuals and firms in microeconomic applications or generally countries in macroeconomic applications over several time periods (Baltagi, 2001). In other words, static panel data regressions are models comprising repeated observations on the same cross section observed for several time periods, which allows us to analyze individual behaviors in repetitive environment (Cameron and Trivedi, 2005).

Panel data provides some advantages by using them (Baltagi, 2001; Cameron and Trivedi, 2005):

1. Increased precision in estimation. This is mainly due to the increased number of observations through pooling of observations for several time periods for each individual.

2. Controlling for unobserved individual heterogeneity and consistent estimation of the fixed effect model.

3. Allowing of learning more about the dynamics of individual behavior than is possible from a single cross section since it provides information on individual behavior both across time and across

We adopted three different panel data approaches in order to analyze relationship between the nonperforming loans and various macro and micro variables: Fixed effects, random effects and dynamic panel data models.

4.3.1.1 Fixed Effects and Random Effects Models

Any analysis that concentrated on capturing the bank specific effects uses a panel data model. Here each cross-sectional unit has a different intercept term though all slopes are the same.

$$y_{it} = \alpha_i + \beta' x_{it} + e_{it} \tag{4.29}$$

The subscript i indexes the banks and the subscript t indexes time. The dependent variable y_{it} is scalar, and the regressor $x_{it}=(x_{1t}, \ldots, x_{kt})$ is a k dimensional vector of explanatory variables. It is assumed that error e_{it} is independent and identically distributed (i.i.d.) with mean zero and finite variance and is uncorrelated across time and individuals. α_i denotes the unobservable bank specific effects and is time invariant.

We can define two separate static panel data models depending on the properties of bank specific effects: Fixed effects and random effects model.

In the fixed effects model α's a are assumed to be fixed parameters, while in random effects it is assumed to be random and it is distributed i.i.d. (Baltagi, 2001). In fixed effects we deal with within estimators, in other words, we focus on differences within individual units. In such a model each bank has its own characteristics that affect the predictor variable but they are assumed to be uncorrelated with other banks' characteristics. And by fixed effects model, we aim to control for this impact on explanatory variables. Also we assume that individual effects are uncorrelated with error terms, when it is the case the random effects model could be more suitable. Random effects model allow variation across entities that is random and uncorrelated with the predictor. It also allows to use time invariant variables in the model unlike fixed effects model.

Within Group (WG) estimators or fixed effects estimators are used to estimate the fixed effect parameters. Taking average over time and subtracting this from y_{it} yield the within model. Through this transformation, we remove the effect of individual characteristics on explanatory variables. We can then estimate the transformation of the model in Equation 4.29 where individual effects are removed by OLS. The transformed model is given as:

$$y_{it} - \bar{y}_i = (x_{it} - \bar{x}_i)'\beta + e_{it} - \bar{e}_i \qquad \textbf{(4.30)}$$

where $\bar{y}_i = \frac{1}{T}\sum_t^T y_{it}$, $\bar{e}_i = \frac{1}{T}\sum_t^T e_{it}$, and $\bar{x}_i = \frac{1}{T}\sum_t^T x_{it}$

WG or fixed effects (FE) estimators are consistent and efficient estimator of β in the model if α's are fixed effects and error terms are iid. WG (or FE) estimators are defined as (Verbeek, 2004):

$$\hat{\beta}_{FE} = \left(\sum_{i=1}^{N}\sum_{t=1}^{T}(x_{it} - \bar{x}_i)(x_{it} - \bar{x}_i)'\right)^{-1}\sum_{i=1}^{N}\sum_{t=1}^{T}(x_{it} - \bar{x}_i)(y_{it} - \bar{y}_i)' \qquad \textbf{(4.31)}$$

The individual specific N piece intercepts are estimated as follows:

$$\hat{\alpha}_i = \bar{y}_i - \bar{x}_i{}'\hat{\beta}_{FE} \qquad \text{i=1,…,N} \qquad \textbf{(4.32)}$$

The random effects model can be given as follows:

$$y_{it} = \mu + \beta' x_{it} + \alpha_i + e_{it} \tag{4.33}$$

where $\alpha_i \sim iid(0, \sigma_\alpha^2)$ and $e_{it} \sim iid(0, \sigma_e^2)$.

As mentioned above in random effects model, both individual specific effects, α_i, which does not vary over time, and error terms, e_{it} are assumed to be i.i.d. Here the error term consists of both random effects and error terms. Although these terms are individually independent and identically distributed, the composite error term displays autocorrelation such that

$$corr(\alpha_i + e_{it}, \alpha_i + e_{is}) = \sigma_\alpha^2 \,/\, (\sigma_\alpha^2 + \sigma_e^2) \quad \text{for } s \neq t \tag{4.34}$$

Therefore, we have a model with an error term which is autocorrelated. Hence, the model should be so transformed that the autocorrelation is removed from the model. We can consistently and efficiently estimate parameters β by using Generalized Least Squares (GLS). The feasible GLS estimator of the random effects model or the random effects estimator can be calculated from Ordinary Least Squares (OLS) estimation of the transformed model (Cameron and Trivedi, 2005).

$$y_{it} - \hat{\lambda}\bar{y}_i = (1 - \hat{\lambda})\mu + (x_{it} - \hat{\lambda}\bar{x}_i)'\beta + v_{it} \tag{4.35}$$

where $\bar{y}_i = \frac{1}{T}\sum_t^T y_{it}$, $\bar{x}_i = \frac{1}{T}\sum_t^T x_{it}$ and $v_{it} = (1 - \hat{\lambda})\alpha_i$ +($e_{it} - \hat{\lambda}\bar{e}_i$) is asymptotically i.i.d. and $\hat{\lambda}$ is consistent for

$$\hat{\lambda} = 1 - \frac{\sigma_e}{\sqrt{\sigma_e^2 + T\sigma_\alpha^2}} \tag{4.36}$$

Note that $\hat{\lambda} = 1$ corresponds to within estimation. The random effects estimator is fully efficient under the random effects hypothesis. However, it is inconsistent when the fixed effects model is the correct model (Cameron and Trivedi, 2005). OLS estimators are consistent, but not efficient.

The feasible GLS estimator or the random effects (RE) estimator of μ and β is defined as (Cameron and Trivedi, 2005):

$$\hat{\delta}_{RE} = \begin{bmatrix} \hat{\mu}_{RE} \\ \hat{\beta}_{RE} \end{bmatrix} = \left(\sum_{i=1}^{N} \sum_{t=1}^{T} (w_{it} - \hat{\lambda}\overline{w}_i)\left(w_{it} - \hat{\lambda}\overline{w}_i\right)' \right).^{-1}$$

$$\sum_{i=1}^{N} \sum_{t=1}^{T} (w_{it} - \hat{\lambda}\overline{w}_i)(y_{it} - \hat{\lambda}\bar{y}_i)' \qquad \textbf{(4.37)}$$

where $w_{it}=[1\ x_{it}]$ and $\overline{w}_i = [1\ \bar{x}_i]$

In the FGLS process, in order to obtain the transformed model, we need to, first, obtain the estimates of σ_e^2 and σ_α^2 in order to calculate $\hat{\lambda}$. The estimate of σ_e^2 can be obtain from WG or fixed effects residuals (Cameron and Trivedi, 2005):

$$\hat{\sigma}_e^2 = \frac{1}{N(T-1)-K} \sum_{i=1}^{N} \sum_{t=1}^{T} ((y_{it} - \bar{y}_i)(x_{it} - \bar{x}_i)'\, \hat{\beta}_{FE(W)})^2 \qquad \textbf{(4.38)}$$

The estimate of σ_α^2 can be obtained from between (B) regression where the error term has variance of $\sigma_\alpha^2 + 1/T\ \sigma_e^2$ (Cameron and Trivedi, 2005):

$$\hat{\sigma}_\alpha^2 = \frac{1}{N-(K+1)} \sum_{i=1}^{N} \left(\bar{y}_i - \hat{\mu}_B - \bar{x}_i'\hat{\beta}_B\right)^2 - \frac{1}{T}\hat{\sigma}_e^2 \qquad \textbf{(4.39)}$$

where $\hat{\beta}_B$ is between estimator, which is defined as (Verbeek, 2004):

$$\hat{\beta}_B = \left(\sum_{i=1}^{N} (\bar{x}_i - \bar{x})(\bar{x}_i - \bar{x})'\right)^{-1} \sum_{i=1}^{N} (\bar{x}_i - \bar{x})(\bar{y}_i - \bar{y})' \qquad \textbf{(4.40)}$$

where $\bar{y} = \frac{1}{NT} \sum_{i=1}^{N} \sum_{t=1}^{T} y_{it}$ and $\bar{x} = \frac{1}{NT} \sum_{i=1}^{N} \sum_{t=1}^{T} x_{it}$.

By applying Hausman test, we can compare the performance of the WG (FE) and the GLS (RE) estimators. The test is applied to the model given in Equation 4.33 and it is tested whether the individual specific effects, α_i, are correlated with explanatory variables or not. If they are correlated, then it is reasonable to use WG (FE) estimator instead of GLS (RE) estimator, which is no longer consistent. But this does not mean that the effects have become fixed. Hence the choice is not between models (i.e. FE model vs RE model) but between estimators for the same model, i.e., the random effects model (Erlat, 2008).

The null hypothesis is the individual effects are uncorrelated with the explanatory variables, in other words,

$$H_0: E(\alpha_i|x_{it}) = 0 \quad \textbf{(4.41)}$$

$$H_1: E(\alpha_i|x_{it}) \neq 0 \quad \textbf{(4.42)}$$

WG (FE) estimator is consistent both under H_0 and H_1, but GLS (RE) estimator consistent and efficient under H_0 but is inconsistent under H_1 (Erlat, 2008). The Hausman test statistic is defined as (Verbeek, 2004):

$$H = (\hat{\beta}_{FE} - \hat{\beta}_{RE})'\left[var(\hat{\beta}_{FE}) - var(\hat{\beta}_{RE})\right]^{-1}(\hat{\beta}_{FE} - \hat{\beta}_{RE}) \quad \textbf{(3.43)}$$

where $var(\hat{\beta}_{FE})$ and $var(\hat{\beta}_{RE})$ are variances of WG (FE) estimator and of GLS (RE) estimator respectively.

H test statistic has an asymptotic Chi-squared distribution with K degrees of freedom, where K denotes the number of elements in β. $var(\hat{\beta}_{FE})$ is defined as follows (Verbeek, 2004):

$$var(\hat{\beta}_{FE}) = \sigma_e^2 \left(\sum_{i=1}^{N}\sum_{t=1}^{T}(x_{it} - \bar{x}_i)(x_{it} - \bar{x}_i)'\right)^{-1} \quad \textbf{(4.44)}$$

Variance of GLS (RE) estimator, $var(\hat{\beta}_{RE})$, is defined as :

$$var(\hat{\beta}_{RE}) = \sigma_e^2 \left(\sum_{i=1}^{N}\sum_{t=1}^{T}(x_{it} - \bar{x}_i)(x_{it} - \bar{x}_i)' + \psi T \sum_{i=1}^{N}(x_{it} - \bar{x})(x_{it} - \bar{x})'\right)^{-1}$$

(4.45)

where $\psi = \frac{\sigma_e^2}{\sigma_e^2 + T\sigma_\alpha^2}$

4.3.1.2 Dynamic Panel Data Model

Generalized least squares, within estimation and ordinary least squares models lose their desired properties when dynamic structure introduced into the model. Dynamic panel data model captures the persistence in dependent variable after introducing the lagged dependent variable into the equation. Hence in such models the speed of adjustment is governed by the coefficient of the lagged dependent variable, y_{it-1}.

We can express the dynamic panel data model as follows:

$$y_{it} = \alpha_i + \beta_1 y_{it-1} + x'_{it}\beta_2 + e_{it}, \qquad |\beta_1|<1 \qquad \textbf{(4.46)}$$

In the model, x_{it} are regressors, α_i are unobserved individual heterogeneity and error e_{it} is independent and identically distributed (i.i.d.) with mean zero and finite variance and is uncorrelated across time and individuals.

By assumption, x_{it} is strictly exogenous, i.e.

$$E\,(e_{it} \mid x_{i1}, ..., x_{iT}, \alpha_i) = 0 \qquad (t = 1, ..., T) \qquad \textbf{(4.47)}$$

But this does not rule out the case that x's are related to α's. Also the lagged dependent variable poses endogeneity problem and it is related with the error term and individual specific effects. Then even if α_i is a random effect, OLS estimation of above equation leads to biased and inconsistent estimation of slope coefficients since the lagged dependent variable $y_{i,t-1}$ is correlated with α_i. Then it is plausible to consider α_i as fixed effects. GLS estimation will also produce inconsistent estimators. Also we know that y_{it} is correlated with e_{it}, then $y_{i,t-1}$ is correlated with $e_{i,t-1}$ and hence mean of the error term, $\bar{e}_i$. Then, this implies that the regressor $(y_{i,t-1} - \bar{y}_i)$ is also correlated with the error term $(e_i - \bar{e}_i)$. Hence, OLS estimation of the within model leads to inconsistent parameter estimates, since the regressor is correlated with the error term (Cameron and Trivedi, 2005).

One immediate problem is to tackle the endogeneity problem due to the correlation of $y_{i,t-1}$ with fixed individual effects, which is called "dynamic panel bias"

(Nickell, 1981). Arellano and Bond (1991) propose a method to consistently estimate the above equation, called difference Generalized Method of Moments (GMM) method. In order to do this, we take the first difference of the equation and hence we eliminate the individual specific effects.

$$\Delta y_{it} = \beta_1 \Delta y_{it-1} + \Delta x'_{it}\beta_2 + \Delta e_{it}, \qquad |\beta_1|<1 \qquad \textbf{(4.48)}$$

However, endogeneity problem still prevails. Hence, the OLS and WG estimators produce inconsistent estimates. This is mainly due to the correlation between Δy_{it-1} and Δe_{it}, which results in a bias in the estimation of the model. In order to fix the endogeneity due to the lagged dependent variable, Anderson and Hsiao (1982) proposed to control endogeneity using higher order lagged dependent variables y_{it-2} and Δy_{it-2} as instruments for Δy_{it-1}. Indeed these are valid instruments, since they are not correlated with $(e_{it} - e_{it-1})$ assuming the errors e_{it} are serially uncorrelated, but correlated with Δy_{it-1}. This suggests that lags of higher orders of the dependent variable are not correlated Δe_{it} .

Hence, it is possible to obtain more efficient estimation through using additional lags of the dependent variable as instruments. However, since the model will then become overidentified, it is necessary to use 2SLS or panel GMM, called the Arellano–Bond estimator (Cameron and Trivedi, 2005). We introduce instruments in line with one step GMM estimation. Arellano and Bond (1991) compared the performance of GMM, OLS, and WG estimators and they found that GMM estimators exhibit the smallest bias and variance.

The validity of instruments as well as the assumption of serial independence of residuals is vital for the consistency of the GMM estimates. Overall validity of instruments can be tested by Sargan specification test (Sargan, 1958). Under the null hypothesis, residuals should be uncorrelated with instruments. Another important assumption needed to be tested is that the errors e_{it} are serially uncorrelated. Arellano and Bond (1991) proposed a test for the hypothesis that differenced errors Δe_{it} are not second order autocorrelated. We should note that in the presence of serial correlation of errors the validity of some instruments can be affected. For example, if the errors are serially correlated of order 1, then dependent variable y_{it-2} becomes endogenous due to the presence of e_{it-1} in Δe_{it} , which makes y_{it-2} invalid as an instrument. Since Δe_{it} is mathematically related to Δe_{it-1} through the e_{it-1} term, negative first-order serial correlation is expected in differences. Hence in order to check for the first-order serial correlation in levels, it is plausible to look for second order correlation in differences. In general it is a reasonable way to check for serial correlation of order s in levels by looking for correlation of order s+1 in differences (Roodman, 2006). Rejection of the null hypothesis that there is no second order correlation implies the existence of the serial correlation for the level of errors. This, in turn, implies that the GMM estimates are invalid.

4.3.2 Nonlinear Panel Data Model

The nonlinear analysis employs a balanced panel data model in order to capture the bank-specific effects and nonlinearity (Hansen, 1999).

$$y_{it} = \alpha_i + \beta_1' x_{it} I(q_{it} \leq \gamma) + \beta_2' x_{it} I(q_{it} > \gamma) + e_{it} \quad \textbf{(4.49)}$$

The subscript i indexes the banks and the subscript t indexes time. The dependent variable y_{it} is scalar, and the regressor x_{it} is a k vector. It is assumed that error e_{it} is independent and identically distributed (iid) with mean zero and finite variance. α_i denotes the unobservable bank specific effect and is time invariant.

I(.) denotes the indicator function that indicates the regime defined by the transition variable q_{it} and the threshold level γ. Hence, depending on whether transition variable is smaller or larger than the threshold value, we have a piecewise linear model and the observations are grouped into two regimes.

We can compactly represent the above equation as follows:

$$y_{it} = \alpha_i + \beta' x_{it}(\gamma) + e_{it} \quad \textbf{(4.50)}$$

where $x_{it}(\gamma) = \binom{x_{it}I(q_{it} \leq \gamma)}{x_{it}I(q_{it} > \gamma)}$ and $\beta = (\beta_1' \; \beta_2')'$

As in the linear fixed effects model, one method to eliminate bank specific effects α_i is to remove bank specific means. Taking averages over time index t produces:

$$\bar{y}_i = \alpha_i + \beta' \bar{x}_i(\gamma) + \bar{e}_i \quad \textbf{(4.51)}$$

where $\bar{y}_i = \frac{1}{T}\sum_t^T y_{it}$, $\bar{e}_i = \frac{1}{T}\sum_t^T e_{it}$, and $\bar{x}_i(\gamma) = \frac{1}{T}\sum_t^T x_{it}(\gamma)$

After taking the difference between y_{it} and $\bar{y}_i$, then we have y_{it}^*:

$$y_{it}^* = \beta' x_{it}^*(\gamma) + e_{it}^* \quad \textbf{(4.52)}$$

where $y_{it}^* = y_{it} - \bar{y}_i$, $x_{it}^*(\gamma) = x_{it}(\gamma) - \bar{x}_i(\gamma)$, and $e_{it}^* = e_{it} - \bar{e}_i$

Let Y*, X*(γ) and e* denote the data stacked over all banks, and then the above equation takes the following form:

$$Y^* = X^*(\gamma)\beta + e^* \quad \textbf{(4.53)}$$

For any given threshold value, the above equation can be estimated by ordinary least squares. Since the least squares estimation of the transition variable requires the minimization problem, we sort the observations on the transition variable. For any given threshold value, we estimate the slope coefficient by ordinary least squares and obtain sum of squared errors for each estimation. The estimator of slope coefficient is:

$$\hat{\beta}(\gamma) = (X^*(\gamma)' X^*(\gamma))^{-1} X^*(\gamma)' Y^* \quad \textbf{(4.54)}$$

And the vector of residuals is:

$$\hat{e}^*(\gamma) = Y^* - X^*\hat{\beta}(\gamma) \tag{4.55}$$

And the sum of squared errors is:

$$S_1(\gamma) = \hat{e}^*(\gamma)'\hat{e}^*(\gamma) \tag{4.56}$$

The smallest value of sum of squared errors yields the optimal value of threshold.

$$\hat{\gamma} = argmin\, S_1(\gamma) \tag{4.57}$$

After $\hat{\gamma}$ value is obtained, the slope coefficient estimate can be easily calculated, $\hat{\beta} = \hat{\beta}(\gamma)$.

After conducting ordinary least squares minimization and selecting threshold value such that it minimizes the sum of squared residuals, in a third step it is important to test for whether the threshold effect is statistically significant or not. The null hypothesis of no threshold effect given Equation 4.49 is as follows:

$$H_0: \beta_1 = \beta_2 \tag{4.58}$$

The threshold value is not identified under the null of linearity. Therefore, the distribution of a standard F-statistic is not chi-square.

Under the null hypothesis of no threshold, the model is:

$$y_{it} = \alpha_i + \beta' x_{it} + e_{it} \tag{4.59}$$

And after the fixed effect transformation it becomes:

$$y_{it}^* = \beta' x_{it}^* + e_{it}^* \tag{4.60}$$

By estimating the above equation by OLS, slope coefficient estimates and sum of squared errors $S_0 = \tilde{e}^{*\prime}\tilde{e}^*$ can be obtained. Then the likelihood ratio test of H_0 becomes:

$$F_1 = \frac{(S_0 - S_1(\hat{\gamma}))}{\hat{\sigma}^2} \tag{4.61}$$

where $\hat{\sigma}^2 = \frac{1}{n(T-1)}\hat{e}^{*\prime}\hat{e}^* = \frac{1}{n(T-1)}S_1(\hat{\gamma})$.

According to the bootstrap procedure outlined in Hansen (1996b), first-order asymptotic distribution and p-values can be constructed.

In a nutshell, it should be noted that the panel data approach constitutes the second building block of our augmented framework and this approach mainly aims to evaluate the soundness of the banking sector under extraordinary but plausible shocks. With a view to exercising this stress testing practice, we test all panel data models in measuring the credit risk, proxied by the nonperforming loans by employing forecasted values for macro indicators derived from the VAR models. The details of this scheme are outlined in the next section.

4.4 Forecasting and Stress Testing

Macro stress tests provide policy makers with information on potential losses of financial system under extraordinary but plausible scenarios. These scenarios often comprise of various external macroeconomic shocks to the economy. In this sense, it is important that a macroeconometric model forms the basis of the stress testing in creating scenarios. Hence, the scenarios produced from a macroeconometric model cover system wide interactions and provide an efficient way to represent all aspects of a possible external macroeconomic shock.

As mentioned before, the VAR models are effective tools in functioning as a base model of a stress test to create such scenarios. They not only deliver the necessary elasticities of various variables but also allow measuring the interaction between different segments of the economy, most notably between real economy and financial system. Hence, by using a VAR model, it is possible to calculate both a forecasted value of a certain variable at time t+1 and the impact of a shocked variable on the other variables in the system. For the calculation of forecasted values, the model is estimated with data up to a certain period of time and the estimated coefficients are obtained. The forecasts for the variables in the model for the future periods are calculated by using derived elasticities.

A VAR(p) process and s step ahead forecast are given in Equation 4.1 and Equation 4.18 respectively. Then, by using estimated VAR parameters, at forecast origin T, an s step ahead forecast can be defined as follow:

$$\hat{y}_{T+s|T} = \hat{A}_1 \hat{y}_{T+s-1|T} + \cdots + \hat{A}_p \hat{y}_{T+s-p|T} \quad \textbf{(4.62)}$$

This s step ahead forecast process will provide the necessary forecasted values of the macroeconomic and macrofinancial variables, which are also employed in the panel data model. For those variables which are used in the panel data model but not in VAR model, one possible way is to use historical data in order to calculate possible variations in these series or to make certain assumptions on their possible growth rates.

The panel data model measures the impact of macroeconomic, macrofinancial and individual financial variables on a bank's portfolio. Like in the VAR estimation process, the panel data model is estimated with data up to a certain period of time and the estimated coefficients are derived. It is possible to calculate the stress on bank's portfolio, here the asset quality of a bank, within the scope of a scenario in play by using the estimated elasticities from the panel data model and the forecasted values from the VAR model and derived values that depend on certain assumptions. This derived distress on bank asset quality is main outcome of the macro stress testing. A possible next step could be calculation of the variation in the bank's capital adequacy ratio due to this distress.

Obviously since we have more than one candidate panel data models we can evaluate their performance in estimating the change in the bank's asset quality. To this end, one can employ several benchmarks to measure the variation in the performance of the models. One such measure is root mean square error (RMSE), which measure of the differences between values estimated and the values actually observed. RMSE can be defined as follow:

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}(y_t - \hat{y}_t)^2}{n}} \quad \textbf{(4.63)}$$

where n denotes the number of forecasted or actual values.

Another measure is mean absolute percentage error (MAPE). MAPE can be defined as follow:

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{(y_t - \hat{y}_t)}{y_t}\right| x100 \quad \textbf{(4.64)}$$

where n denotes the number of forecasted or actual values.

When two forecast accuracy measure is compared, it is observed that RMSE is not a unit free measure unlike MAPE. On the other hand, MAPE is a unit free measure, but it places a higher penalty on forecasts that exceed the actual value. In other words, there is a lower bound of one hundred percent but no upper bound.

To sum up, we follow the procedure below:

1. The estimated VAR model is used to forecast the values of industrial production, consumer price index, interbank overnight deposit rate and total loans of the banking sector for the period from 2012:01 to 2012:12.

2. Estimate the panel data model up to 2011:12, which is discussed in the following subsection, and obtain the estimated elasticities. Then, using these

elasticities and the one step ahead forecasts from the VAR model, estimate nonperforming loans for the period from 2012:01 to 2012:12.

3. Using RMSE and MAPE, evaluate the performance of panel data models in estimating the next period's nonperforming loans and choose the best performing model as the baseline model.

4.5 Concluding Remarks

In this chapter, the methodological approaches are discussed. In a nutshell, our modelling cycles can be summarized as follows:

First, linear and then nonlinear VAR models are presented. These models mainly focus on interactions between macroeconomic and macrofinancial variables. By using these models, we obtain the forecasted values for the macroeconomic and macrofinancial variables. We make a decision between linear and nonlinear models based on their performance in forecasting macroeconomic and macrofinancial variables.

Second, several panel data models are discussed. In order to predict the future values of the nonperforming loans, we use fixed effects, random effects, dynamic and nonlinear fixed effects panel data models through employing forecasted macroeconomic and macrofinancial variables that are obtained in step 1. These models aim to specify the determinant of the asset quality of banks, proxied by nonperforming loans. In order to test the resilience of the banking sector to macro shocks, both VAR and panel data models are considered as models connected to each other.

Then, we evaluate their prediction performances of the panel data models by several error measurement criteria and conclude which panel data model performs best.

CHAPTER 5

EMPIRICAL RESULTS

5.1 Introduction

This chapter mainly discusses the empirical results of the VAR and panel data models, which are explained in detail in Chapter 4. Within this context, the main aim of this chapter is to predict nonperforming loans and macro stress test the Turkish banking sector under the proposed scenarios. As explained in Chapter 4, in order to construct scenarios and obtain forecasted values for the macroeconomic and macrofinancial variables, we estimate two VAR models: A linear and a nonlinear VAR model. In the next step we adopt panel data approach to explain the determinants of asset quality of banks. For the sake of being cautious, we employ several panel data models, fixed effects, random effects, dynamic and nonlinear panel data models. According to the empirical results, nonlinear VAR and nonlinear panel data models provide better results than their linear alternatives.

The plan of this chapter is as follows. Section 5.2 presents the estimation of VAR models. In this section we use both linear and nonlinear models. By these models, we evaluate the interaction between business cycles and financial cycle. Panel data models are analyzed in Section 5.3. The section first discusses the estimates of linear models, which include fixed effects, random effects and dynamic panel models. After obtaining the results of the linear models, we focus on a nonlinear panel data model. The empirical results suggest there is a significant interaction among macro indicators. And several macroeconomic and bank specific variables are good indicators in explaining developments in asset quality of banks. Section 5.4 discusses forecasting and macro stress testing.

5.2 VAR Model

5.2.1 Data

Our analysis pertains to Turkish economy and we use monthly data set for the period 2002:12-2012:12. The analysis employs industrial production, consumer price index, interbank overnight deposit rate and total loans of the banking sector. The macro stress testing studies based on a VAR framework mostly include these macroeconomic variables and at least one macrofinancial variable or banking sector soundness indicator (for example, Jacobson et al., 2005; de Graeve et al., 2008; Dovern et al., 2010).

The data on industrial production index as a proxy for GDP and consumer price index are available on the website[5] of Central Bank of the Republic of Turkey. Interbank overnight deposit rate is drawn from Bloomberg. Total loans of the banking sector to private sector data is obtained from Banking Regulation and Supervision Authority's online database[6]. All the variables are seasonally adjusted except interest rates. We use annual growth rate of industrial production, CPI and loans series.

The descriptive statistics is given in Table 4. The macroeconomic and macrofinancial times series have an erratic structure as it is discussed in detail in Chapter 2.

Table 4. Descriptive Statistics

	Industrial production	CPI	O/N Interest Rate	Loans
Mean	6.0901	8.4509	15.5598	34.4783
Standard Deviation	9.1376	1.8090	9.0229	16.2859
Skewness	-1.1028	-0.3426	1.4386	0.0881
Kurtosis (excess)	1.8172	-0.2838	2.2807	-0.5597
Jarque-Bera	37.0929	2.4983	67.9648	1.5640
Prob.	0.0000	0.2867	0.000	0.4574

[5] http://evds.tcmb.gov.tr.

[6] http://ebulten.bddk.org.tr/ABMVC.

As discussed in detail in Chapter 3, during the analysis period, due to the implementation of economic policies towards stability and growth after 2000-2001 crises, it can be observed that, in the analysis period, there is a constant decrease in interest rates and constant expansion of total loans to private sector. However, for the year 2006 when global economic fluctuation occurred and for the years 2008-2009 when the global financial crisis erupted, the trend seems to be temporarily reversed. The mac

5.2.2 Linear VAR Model Results

In this chapter we estimate both linear and nonlinear VAR models and this subsection linear VAR model results are presented.

5.2.2.1 Estimates

The section discusses the estimates of a four-variable VAR model, which comprises industrial production, interbank overnight deposit rate, consumer price index and total loans of the banking sector in order to investigate the effects of a credit shock to macroeconomic stability. Here we try to measure the interaction between business cycle proxied by industrial production and financial cycle proxied by annual credit growth.

We estimate a VAR model as follows:

$$\begin{pmatrix} industrial\ production_t \\ cpi_t \\ O/N\ interest\ rate_t \\ total\ loans_t \end{pmatrix} = \theta_i \begin{pmatrix} industrial\ production_{t-1} \\ cpi_{t-1} \\ O/N\ interest\ rate_{t-1} \\ total\ loans_{t-1} \end{pmatrix} + v_t \tag{5.1}$$

First, we test for unit root (Table 5) by using augmented Dickey-Fuller (ADF), Philips-Perron (PP) and the Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) tests.

According to the ADF and PP test results, annual growth rates of industrial production, CPI and loans series are nonstationary. However, KPSS test results indicate stationarity in these series. Overnight interest rate is nonstationary according to the three test results. The mixed results may be due to the length of the time period of this study.

Table 5. Unit Root Tests: ADF, PP and KPSS Tests

(annual growth rates except O/N interest rates)		**t/LM statistics**	**Critical values**		
			1%	**5%**	**10%**
Industrial prod.	ADF	-1.764	-4.055	-3.456	-3.154
	PP	-2.793	-4.044	-3.451	-3.151
	KPSS	0.095	0.216	0.146	0.119
CPI	ADF	-2.017	-4.055	-3.456	-3.154
	PP	-2.969	-4.044	-3.451	-3.151
	KPSS	0.066	0.216	0.146	0.119
O/N Interest Rate	ADF	-2.387	-4.055	-3.456	-3.154
	PP	-2.911	-4.044	-3.451	-3.151
	KPSS	0.129	0.216	0.146	0.119
Loans	ADF	-1.732	-4.055	-3.456	-3.154
	PP	-2.767	-4.044	-3.451	-3.151
	KPSS	0.109	0.216	0.146	0.119

It is worth to note that we obtain different findings from the employed unit root tests and, hence, the unit test results given in Table 7 could be misleading due to erratic structure of the data, possible structural breaks and also more importantly possible nonlinearities. It is well known that during an economic crisis macroeconomic variables decline sharply but not rise swiftly. Therefore, since the unit root tests are constructed under the linearity assumption, it should be noted that their reliability can be questionable.

Next, in order to decide on the order of the VAR model, we apply log likelihood (LR) test and employ AIC, BIC, and HQ information criteria. Test statistics are given in Table 6. All information criteria, i.e. AIC, BIC and HQ, suggest a VAR(1) model, while LR test results signal a VAR(3) model. Hence, we decide to use a VAR model of order 1.

Table 6. Lag Selection

Lag	LR	AIC	SIC	HQ
0	n.a.	2383.3	2393.5	2387.3
1	25.69	**1621.1***	**1670.3***	**1639.6***
2	23.37	1635.7	1720.8	1665.6
3	**14.65***	1651.2	1768.6	1688.8
4	43.12	1677.5	1823.2	1718.9
5	17.25	1678.5	1847.6	1718.8
6	18.28	1706.2	1893.3	1739.9
7	8.64	1742.7	1941.2	1763.3
8	24.33	1800.0	2002.2	1799.7
9	33.94	1843.7	2040.3	1813.3
10	20.28	1879.0	2058.6	1807.1
11	33.30	1959.4	2108.1	1832.0
12	47.47	2017.4	2117.7	1817.1

* denotes the min value.

We need to take into consideration the possible breaks and outliers in the data. In order to test whether there is a structural break, we adopt Bai-Perron structural change approach (Bai-Perron, 2003). Therefore, as suggested Bai and Perron, we consider the supF type test of no structural break (m=0) versus m=k breaks. They also propose a test for *s* versus *s*+1 breaks which is called supF(s+1|s). The method requires the application of (s+1) test of the null hypothesis of no structural change versus the alternative hypothesis of a single change. A rejection of null hypothesis in favor of a model with (s+1) breaks is realized if the overall minimal value of the sum of squared residuals is smaller enough than the sum of squared residuals from the s breaks model. We also use information criteria to determine the number of breaks, which are Bayesian Information Criterion and a modified Schwarz criterion. The two problems with information criteria is that Bayesian Information Criterion may behave badly when there is serial correlation and modified Schwarz criterion may underestimate the number of breaks.

Table 7. Bai-Perron Structural Change Test Results

Variables	Number of breaks			Breaks
	BIC	**SIC**	**F test (significance %5)**	
Industrial production	5	4	4	2005:12 2008:02 2009:11 2010:03
Inflation	4	0	0	-
O/N Interbank Rate	5	2	2	2009:11 2010:10
Total loans	5	3	1	2004:03 2004:08 2006:05

In order to implement the test, we consider the structural stability of the AR(1) representation of the series. We allow up to 5 breaks and the first issue to be considered is the determination of the number of breaks. Criteria for the determination of number of breaks and the estimated break dates are given the Table 7.

We find that industrial production, O/N interbank rate and total loans are respectively subjected to four, two and three structural breaks respectively. Inflation is found not to be subject to any structural break in the analysis period. Considered break dates spans the periods where global financial fluctuations occur in 2006 and the global financial crisis erupts in 2009 and onwards. The years 2004 and 2005 represent the years just after the 2000-2001 crises and may reflect the effects of structural reforms in these years.

Table 8 presents the diagnostic test results of the linear VAR model. RSS and adj R^2 denote residual sum of squares and adjusted R^2. Table 8 also reports the multivariate LM test statistics (LM_{AR}) for the hypothesis of no serial correlation against serial correlation up to 12 lags, the chi square test statistic (X^2_{HET}) for the hypothesis of no heteroscedasticity and the chi-square test statistics for normality where $X^2_{Skewness}$, $X^2_{Kurtosis}$ and $X^2_{Jarque\text{-}Bera}$ denote respectively chi-square test statistics for skewness, kurtosis and Jarque-Bera tests.

It is possible to observe from Table 8 that the null hypothesis of no first order autocorrelation cannot be rejected at 5 percent significance level. Test results for higher autocorrelation indicate existence of some residual serial correlation problem at order of 12. This may be due to the fact that the macro series are in the form of annual percentage change. Considering the heteroscedasticity problem, chi square test statistics is statistically significant and the null hypothesis of no heteroscedasticity cannot be rejected at 5 percent significance level. The results of skewness test suggest that the distribution of data is symmetric to a large extent. But kurtosis test results indicate the existence for excess kurtosis, which leads to the rejection of the null hypothesis of normal distribution.

Table 8. Diagnostic Test Results of Linear VAR					
Statistics	**Industrial Production**	**Inflation**	**Interest Rate**	**Total Loans**	**VAR**
RSS	0.1265	0.0062	138.74	0.1252	
Adj.R^2	0.8451	0.801377	0.9492	0.9516	
Autocorrelation					
$LM_{AR}(1)$					21.59 (0.1571)
$LM_{AR}(2)$					13.49 (0.6363)
$LM_{AR}(3)$					17.04 (0.3831)
$LM_{AR}(4)$					16.02 (0.4519)
$LM_{AR}(5)$					16.35 (0.4285)
$LM_{AR}(6)$					11.94 (0.748)
$LM_{AR}(7)$					17.39 (0.3608)
$LM_{AR}(8)$					21.89 (0.1468)
$LM_{AR}(9)$					23.02 (0.1132)
$LM_{AR}(10)$					14.04 (0.5959)
$LM_{AR}(11)$					10.49 (0.8401)
$LM_{AR}(12)$					79.44 (0.0000)
Heteroscedasticity					
X^2_{HET}					269.20 (0.9544)
Normality					
$X^2_{Skewness}$	-0.3369 (0.1549)	0.0308 (0.8964)	-0.2644 (0.2641)	0.9526 (0.0001)	19.47 (0.0006)
$X^2_{Kurtosis}$	7.57 (0.0000)	3.37 (0.4325)	5.24 (0.0000)	7.03 (0.0000)	188.30 (0.0000)
$X^2_{Jarque\text{-}Bera}$	95.19 (0.0000)	0.6331 (0.7287)	23.53 (0.0000)	88.42 (0.0000)	135.60 (0.0000)

Note: p-values are given in parenthesis.

Figure 11 plots the stability condition check results.

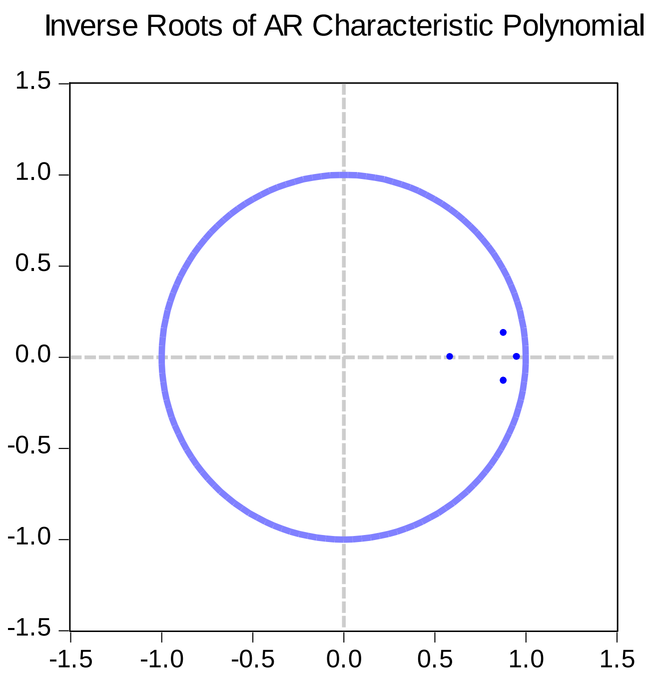


Figure 11: Inverse Roots of AR Characteristic Polynomial

In order to have a stable VAR system, the eigenvalues (i.e. the characteristic roots of the coefficient matrix) given in Equation 4.7 have modulus less than 1. The number of characteristic roots will be np, where n is the number of endogenous variables, which is 4 and p is the largest lag, which is 1. Stability condition check results indicate that the estimated VAR is stable since all roots have modulus less than one and lie inside the unit circle.

We consider possible structural breaks and outliers in the data. In this regard, considering the Bai-Perron structural break analysis results and graphical analysis of series, we focus on three possible structural break periods. Hence three intercept dummy variables are constructed in order to size the effects of fluctuations and crises. First dummy variable takes the value 1 for the period 2004:3 -2004:4 and zero otherwise. Second dummy variable takes the value 1 for the period 2006:5-2006:6 and zero otherwise. Third dummy variable takes the value 1 for the period 2008:11 -2010:3 and zero otherwise. Also, slope dummy variables are formed by multiplying each intercept dummy variable by each of the explanatory variables (in this regard, dummy times the name of the explanatory variable indicates the slope dummy variable for that variable, for example Dummy08-10*CPI denotes the slope dummy variable, which is obtained by the intercept dummy for the period 2008:11 -2010:3 times the variable CPI). The effects of structural breaks are analyzed in detail in Appendix A.

We construct alternate models by checking various combinations, which are composed of either only intercept or only slope dummy variables or altogether across different structural break periods. When we compare the performance of these models based on Akaike information criterion, we observe that the best model is the one that includes both intercept and slope dummy variables that takes the value 1 for the period 2008:11 -2010:3 and zero otherwise. As we will discuss in detail later, after taking the possible structural breaks into account, we apply Tsay's nonlinearity test to check whether any nonlinearity still exists in the data, and we find that test statistics is statistically significant under the null hypothesis of linearity.

The estimation results are presented in Table 9.

In the banking sector loans equation, most of the coefficient of the industrial production is statistically significant. Although the most of the variation in banking sector loans explained by own values, as it will be discussed in subsection 5.2.2.2, second major component in explaining the variation is industrial production. This can be interpreted as sign of first round effects. Hence, macroeconomic shocks represented by changes in industrial production may affect the banking sector.

Table 9. Linear VAR Estimation Results				
	Dependent Variables			
	Industrial Production	**CPI**	**O/N Interbank Rate**	**Loans**
Industrial production	0.6622***	-0.0258	0.0196	0.1699**
CPI	-0.5664**	0.8647***	0.1786**	-0.5085*
O/N interest rate	0.0723	-0.0185	0.8895***	0.2118**
Loans	0.0052	0.0189**	0.0227**	0.8801***
Constant	6.1423**	0.8971	-1.1333	4.6772*
Dummy08-10	15.0396*	-4.5600**	-4.7197	7.1084
Dummy08-10*Ind.Prod	0.4149**	0.0492	0.0437	-0.0417
Dummy08-10*CPI	-1.7313	0.6712**	0.2303	-0.7236
Dummy08-10*Int.Rate	-1.2321	0.2353	0.7511**	-1.0641
Dummy08-10*Loans	0.6096*	-0.1999**	-0.2878**	0.4820
df	*98*	*98*	*98*	*98*
Sum of squared residuals	*1273*	*63*	*138*	*1434*
AIC for VAR	*573.4*			

*,**,*** indicate respectively 10, 5 and 1 percent significance levels

However, in the industrial production equation, the coefficient of banking sector loans is not statistically significant, which is not surprising given the fact that the significant proportion of the variation in industrial production is due to its own values. On the other hand, the coefficient of the interaction term between banking sector loans and the crisis dummy (i.e. the slope dummy variable formed by multiplying intercept dummy variable by the related explanatory variable) is statistically significant, which may indicate evidence for feedback effects from financial system to the real side of the economy

Considering that it may be difficult to interpret the estimated coefficients of the VAR model, in the next section, the variance decomposition results are provided in order to provide a more clear-cut picture.

5.2.2.1 Variance Decompositions

The results of the variance decompositions confirmed the results discussed before. The variance decompositions results are given Table 10, Table 11, Table 12 and Table 13.

When we analyze the error variance of the industrial production, we see that only about 14 percent of the error is due to all other variables in the system after 24 months. In particular, only about 1 percent of the variation can be attributable to the banking sector loans. This finding shows that the feedback effects i.e. the effects of banking sector on real sector is limited.

Considering the variation in the inflation, the main explanatory power is attributable to the inflation itself. At 24 month horizon, about 10 and 14 percent of the error in the forecast of the inflation can be attributed to the industrial production and total loans respectively. This finding is consistent with the theoretical expectation that supply side factors are effective in determining price developments.

Also for the overnight interest rate, most of the variation comes from the variable itself. At 24 month horizon, about 14 percent of the error in the forecast of the interest rate can be explained by the industrial productions, while at the same horizon 11 and 17 percent of the error of the overnight interest rate is attributable to the inflation and the banking sector loans respectively. Hence, in boom periods of the business cycle proxied by the industrial production, the interest rate tends to be higher in line with theory.

Main explanatory power of error variance of the banking sector loans is mainly attributable to its own shocks. However, the proportion which is explained by own shocks rapidly declines at longer forecast horizons and the industrial production starts to explain almost the 41 percent of variation. Hence the first round effects, i.e. the effects of real sector on banking sector become dominant factor after thirteen months. Third and fourth contributors to the banking sector loans' error variance are inflation and interest rate and their contribution is limited respectively to about 11% and 14% at 24-month horizon. Contrary to theoretical expectations that the one of the major determinant of demand for loans, the effect of interest rates on loans is limited.

Table 10. Percent of Variation in the Industrial Production Explained by Each Variable

Lag (month)	Industrial Production	Inflation	O/N Interest Rate	Loans
1	100	0	0	0
2	99.010	0.95	0.038	0.002
3	97.272	2.605	0.121	0.002
4	95.280	4.471	0.241	0.009
5	93.352	6.232	0.381	0.036
6	91.649	7.733	0.528	0.09
7	90.225	8.932	0.673	0.171
8	89.077	9.842	0.807	0.275
9	88.177	10.503	0.925	0.395
10	87.488	10.963	1.026	0.523
11	86.969	11.270	1.110	0.651
12	86.587	11.463	1.177	0.773
13	86.310	11.577	1.228	0.885
14	86.113	11.637	1.266	0.984
15	85.974	11.664	1.293	1.068
16	85.878	11.672	1.311	1.138
17	85.813	11.67	1.323	1.194
18	85.767	11.665	1.330	1.238
19	85.736	11.660	1.334	1.271
20	85.713	11.656	1.336	1.295
21	85.696	11.656	1.336	1.312
22	85.683	11.657	1.336	1.324
23	85.672	11.661	1.336	1.331
24	85.663	11.666	1.335	1.336

Table 11. Percent of Variation in the Inflation Explained by Each Variable				
Lag (month)	**Industrial Production**	**Inflation**	**O/N Interest Rate**	**Loans**
1	4.194	95.806	0	0
2	6.251	93.316	0.025	0.408
3	7.623	91.114	0.067	1.195
4	8.371	89.283	0.113	2.233
5	8.657	87.765	0.152	3.425
6	8.646	86.476	0.181	4.698
7	8.472	85.341	0.197	5.989
8	8.238	84.309	0.203	7.250
9	8.017	83.344	0.201	8.438
10	7.852	82.428	0.197	9.522
11	7.769	81.553	0.196	10.482
12	7.772	80.718	0.202	11.308
13	7.858	79.925	0.219	11.998
14	8.015	79.178	0.251	12.557
15	8.225	78.481	0.297	12.997
16	8.472	77.836	0.358	13.333
17	8.739	77.246	0.433	13.582
18	9.013	76.710	0.520	13.758
19	9.281	76.226	0.615	13.877
20	9.537	75.792	0.718	13.953
21	9.774	75.405	0.824	13.997
22	9.990	75.061	0.932	14.017
23	10.182	74.756	1.040	14.022
24	10.351	74.488	1.145	14.016

Table 12. Percent of Variation in the O/N Interbank Rate Explained by Each Variable				
Lag (month)	**Industrial Production**	**Inflation**	**O/N Interest Rate**	**Loans**
1	0.028	4.130	95.842	0
2	0.117	7.011	92.615	0.258
3	0.337	9.708	89.097	0.858
4	0.631	11.981	85.629	1.760
5	0.985	13.742	82.375	2.898
6	1.40	14.994	79.406	4.200
7	1.881	15.788	76.735	5.595
8	2.433	16.196	74.353	7.018
9	3.056	16.295	72.233	8.417
10	3.744	16.160	70.348	9.748
11	4.490	15.860	68.669	10.981
12	5.281	15.451	67.171	12.096

Table 12. Percent of Variation in the O/N Interbank Rate Explained by Each Variable (continued)				
13	6.104	14.981	65.832	13.083
14	6.944	14.486	64.632	13.938
15	7.786	13.993	63.557	14.664
16	8.618	13.520	62.594	15.269
17	9.426	13.079	61.732	15.763
18	10.202	12.677	60.962	16.159
19	10.938	12.316	60.276	16.47
20	11.628	11.996	59.667	16.708
21	12.271	11.715	59.129	16.886
22	12.863	11.469	58.654	17.014
23	13.405	11.255	58.238	17.102
24	13.898	11.068	57.874	17.159

Table 13. Percent of Variation in the Banking Sector Loans Explained by Each Variable

Lag (month)	Industrial Production	Inflation	O/N Interest Rate	Loans
1	10.279	0.007	0.395	89.319
2	16.431	0.508	0.946	82.114
3	21.92	1.447	1.657	74.975
4	26.466	2.646	2.472	68.415
5	30.082	3.945	3.346	62.627
6	32.887	5.228	4.244	57.641
7	35.030	6.417	5.142	53.411
8	36.647	7.472	6.022	49.858
9	37.856	8.373	6.874	46.897
10	38.751	9.119	7.689	44.441
11	39.407	9.718	8.462	42.414
12	39.882	10.185	9.188	40.746
13	40.220	10.536	9.866	39.378
14	40.457	10.791	10.494	38.258
15	40.619	10.965	11.072	37.343
16	40.725	11.076	11.602	36.597
17	40.791	11.138	12.083	35.987
18	40.828	11.163	12.519	35.490
19	40.844	11.162	12.910	35.084
20	40.846	11.142	13.260	34.752
21	40.838	11.112	13.572	34.479
22	40.823	11.075	13.848	34.254
23	40.804	11.035	14.093	34.068
24	40.783	10.995	14.308	33.914

5.2.3 Nonlinear VAR Model Results

In order to analyze the effect of credit cycles on macroeconomic stability under different credit regimes, we follow the approach that is introduced by Tsay (1998).

First, we apply Tsay's nonlinearity test. To do this, again we consider structural breaks and use dummy variables in the model. In the previous section, we find that controlling for the structural break gives us the best linear VAR. This structural break takes place in the period from November 2008 to March 2010 due to the global crisis and the extraordinary measures taken against it both abroad and in Turkey. We check whether there still exists any nonlinearity in the data after controlling for the structural change for the period from November 2008 to March 2010.

Given that the order of the VAR model is 1, we test all the variables, i.e. industrial production index, inflation, overnight deposit rate and banking sector's total loans, in the model. The p values of significant test statistics are shaded in Table 14. The best transition variable is inflation and the delay parameter is 10. The second best transition variable is interbank overnight deposit rates and the related delay parameter is 1. The short-term interest rate is the main monetary policy tool, which is effectively used after the introduction of inflation targeting regime, and it is effective in determining the cycles both in financial sector and real economy. Therefore, we prefer to choose the overnight interest rate as the transition variable.

Table 14.Results of the Threshold Test

Lag	m0[1]	Variables[2]							
		Industrial production		CPI		Interest Rate		Loans	
		C(d)[3]	p-value	C(d)[3]	p-value	C(d)[3]	p-value	C(d)[3]	p-value
1	40	23.07	*0.98524*	29.09	*0.8991*	70.47	***0.00207***	23.34	*0.98354*
1	50	21.39	*0.99299*	26.64	*0.94804*	57.98	*0.03276*	17.05	*0.99944*
2	40	20.33	*0.99588*	25.26	*0.96658*	38.45	*0.54031*	22.84	*0.98661*
2	50	19.7	*0.99707*	24.23	*0.97678*	52.32	*0.09185*	27.79	*0.92775*
3	40	19.46	*0.99743*	32.62	*0.78981*	48.08	*0.17822*	28.07	*0.92204*
3	50	19.78	*0.99693*	30.85	*0.85017*	45.13	*0.26611*	24.3	*0.97621*
4	40	20.63	*0.9952*	27.48	*0.93365*	42.99	*0.34438*	32.08	*0.80957*
4	50	20.92	*0.99443*	26.42	*0.95134*	45.09	*0.26733*	24.73	*0.97217*
5	40	23.92	*0.97933*	27.81	*0.92741*	38.05	*0.55829*	29.24	*0.89527*
5	50	19.63	*0.99718*	25.52	*0.96345*	42.67	*0.35698*	21.44	*0.99285*
6	40	15.72	*0.9998*	24.48	*0.97453*	41.45	*0.40723*	28.41	*0.91474*
6	50	17.26	*0.99936*	19.79	*0.99692*	46.42	*0.22474*	22.69	*0.98744*
7	40	7.62	*1*	24.05	*0.97829*	40.44	*0.45094*	32.35	*0.79969*
7	50	7.55	*1*	23.46	*0.98271*	41.21	*0.41762*	27.96	*0.92428*
8	40	7.61	*1*	22.13	*0.99015*	41	*0.42649*	32.65	*0.78903*
8	50	7.06	*1*	25.86	*0.95923*	40.68	*0.44016*	35.28	*0.68263*
9	40	20.59	*0.9953*	49.04	*0.15476*	44.24	*0.29724*	39.54	*0.49062*
9	50	19.36	*0.99758*	60.09	*0.02148*	46.38	*0.22592*	35.07	*0.69144*
10	40	38.87	*0.52103*	88.43	***0.00002***	50.83	*0.11721*	47.8	*0.18538*
10	50	26.14	*0.9554*	63.36	*0.01075*	43.86	*0.31132*	38.52	*0.53712*
11	40	28.1	*0.92149*	60.52	*0.01967*	59.52	*0.02411*	41.62	*0.40014*
11	50	27.32	*0.9365*	60.16	*0.02116*	60.83	*0.01842*	38.2	*0.55171*
12	40	29.53	*0.88793*	68.89	*0.00303*	67.86	*0.00387*	50.56	*0.12237*
12	50	29.15	*0.8976*	64.18	*0.00897*	58.78	*0.02798*	49.2	*0.151*

Notes:

1) m0 indicates the starting point of the recursive least squares estimation *and equals to 3 or 5 times the square root of n, number of observations.

2) Industrial production index, consumer price index and banking sector total loans are logged differenced indicating 12-month change.

3) C(d) test statistic check whether the predictive residuals, obtained from recursive least squares estimation, are white noise under the null hypothesis of linearity. please check Equation 4.31 and the related explanation

When lag length and the number of regimes are fixed, in a nutshell, AIC procedure asymptotically boils down to selecting the model with the smallest generalized residual variance through using the conditional least squares method. Given lag length and delay parameter, we find the threshold value for overnight interest rates: 10.1 percent.

A graph for the threshold values is given in Figure 12. A visual inspection also provides some idea about the optimal threshold value. Accordingly, the dispersion of the interest rates suggests that there may be different regimes. It should be reminded that at the beginning of the global crisis, the interbank overnight deposit rate is around 15 percent.

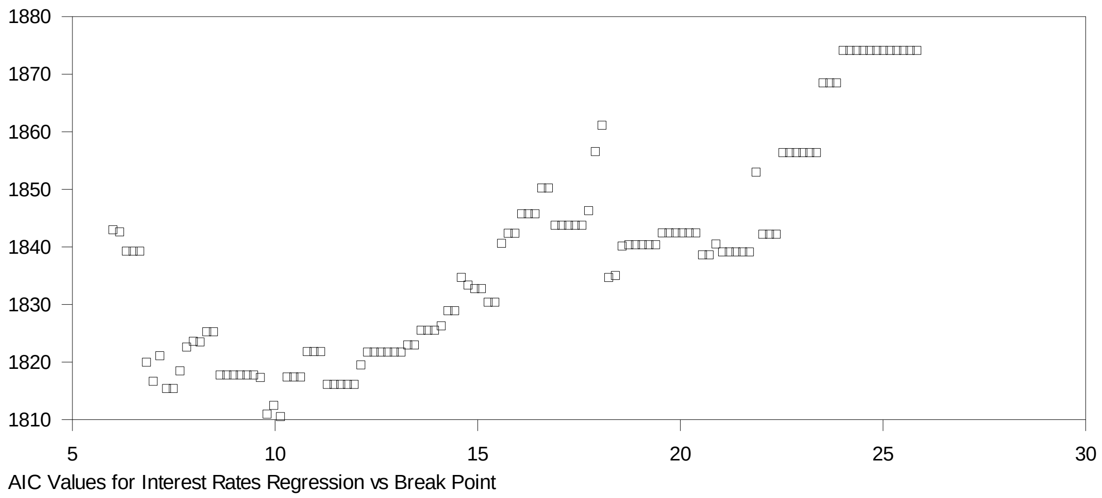


Figure 12: Threshold values vs AIC values

After obtaining threshold value, we implement a piecewise linear estimation method for the VAR regression given in Equation 4.22. In line with the obtained results from linear VAR modelling, again we control for structural breaks only for the global crisis period as we did in nonlinearity tests and determining the threshold value. Intercept and slope dummy variables are included in the model together or separately. No structural break case is also considered. According to the AIC values, the best linear VAR model is the one that includes both intercept and slope dummy variables for the period 2008:11 -2010:3.

For both low and high interest rate regimes, the regression results produce different coefficient estimates. The estimation results for both low and high credit growth regimes are given in Table 15 and Table 16 respectively.

For the low interest rate regime, in the total loans equation, the coefficient of the industrial production is statistically significant. The estimation results for the banking sector loans equation are akin to linear VAR estimation results given in Table 9. In this sense, macroeconomic shocks represented by changes in industrial production affect the banking sector, which constitutes evidence for the first round effect. Again as it is the case for the linear VAR model, there is some significant finding for the feedback effects from financial system to the real side of the economy. In the industrial production equation, the coefficient of the interaction term between banking sector loans and the crisis dummy (i.e. the slope dummy variable formed by multiplying intercept dummy variable by the related explanatory variable) is statistically significant. This implies that the banking sector loans starts to play an effective role in determining the industrial production after the global financial crisis.

Table 15. Nonlinear VAR Estimation Results: Low Interest Rate Regime				
	Dependent Variables			
	Industrial Production	**CPI**	**O/N Interbank Rate**	**Loans**
Industrial production	0.7207***	-0.0213	-0.0848*	0.2263***
CPI	-0.0357	0.8972*	0.4541***	-0.4149*
O/N interest rate	0.2855	-0.2343	-0.1692	0.2028
Loans	0.0294	0.0401	0.1144***	0.8466**
Constant	-0.6337	1.3493	2.4953	4.3882
Dummy08-10	9.5656	-6.3373	-5.7869	-0.7998
Dummy08-10*Ind.Prod	1.2175*	0.2711	0.1397	0.2109
Dummy08-10*CPI	-5.3610**	-0.4498	-0.2861	-1.8905
Dummy08-10*Int.Rate	2.4550	1.3776	1.4946	0.7310
Dummy08-10*Loans	0.9836*	-0.0082	-0.1565	0.8097***
df	*30*	*30*	*30*	*30*
Sum of squared residuals	*196.5*	*30.88*	*44.66*	*85.77*
AIC for VAR	*573.6*			

*,**,*** indicate respectively 10, 5 and 1 percent significance levels

Table 16. Nonlinear VAR Estimation Results: High Interest Rate Regime				
	Dependent Variables			
	Industrial Production	**CPI**	**O/N Interbank Rate**	**Loans**
Industrial production	0.6188***	-0.0286*	0.0004	0.1077
CPI	-1.1192**	0.8645***	0.1151	-0.7874
O/N interest rate	0.0781	-0.0731***	0.9324***	0.2169
Loans	0.0094	0.0130*	0.0184*	0.8925***
Constant	11.2347**	2.2051***	-0.9157	7.1403
Dummy08-10	27.7993	-9.5926**	-1.0753	14.4900
Dummy08-10*Ind.Prod	1.0575*	-0.0241	0.0221	0.1364
Dummy08-10*CPI	0.2726	1.3475**	-0.9798	-1.3376
Dummy08-10*Int.Rate	-2.1936	0.0286	0.8056	-1.6008
Dummy08-10*Loans	0.3425	-0.2015*	-0.0572	0.7771
df	*58*	*58*	*58*	*58*
Sum of squared residuals	*994.70*	*22.62*	*48.20*	*1322.73*
AIC for VAR	*573.6*			

*,**,*** indicate respectively 10, 5 and 1 percent significance levels.

For the high interest rate regime, the significance of the first round effects from the real sector to the financial system disappears (Table 16). As regard to the second round effects, there is no significant finding. One legitimate explanation for this could be that the estimation results are likely to suffer from the limited size of the degrees of freedom, which is not avoidable considering the length of the time period of this study.

One remarkable finding obtained from both linear and nonlinear VAR results is that in the total loans equation the coefficient of overnight interest rates is not statistically significant or its sign is not compatible with the economic theory. This suggests that interest rates have no effect on banks' decision in granting credit, which is contradictory to economic intuition. Considering the analysis period, it starts just after the launch of economic program, main component of which is to establish fiscal discipline by increasing the primary surplus and bringing the high public sector borrowing requirement to sustainable levels, and also to strengthen the banking sector's fundamentals through forcing banks to increase their capital to required adequacy levels. Hence, as these structural targets were achieved gradually, the pressure of high public sector borrowing requirement on banking sector disappeared and banks needed to undertake their intermediary activities such as granting credit to private sector.

Until the elimination of fiscal distortion to the effective functioning of the financial system, the banks preferred to finance public borrowing instead of lending to the private sector due to high returns. Hence, they became the primary buyer of public debt and, in this sense, they acted as "lazy banks". Due to the dominance of public sector in financial system, the financial development realized in a poor and inefficient way in 1990s (İsmihan et al., 2013; İsmihan and Özkan, 2012; Hauner, 2009).

But after the crises and the launch of the economic program, a transformation occurred in the composition of assets by the banking sector with the return of banks to their intermediation activities and credit supply increased. Credit demand also increased as the increase in deferred consumption and investment expenditures fed into demand for loans with the restoration of the stability in financial markets and decreased macroeconomic uncertainties. In a nutshell, from the beginning of the analysis period to the financial turmoil in May-June 2006, it is possible to say that structural factors and financial deepening are major factors in determining the credit supply and demand, and therefore, the elasticity of bank loans to interest rate is low.

Interest rate pass-through may also play an important role in this process. In his study analyzing pass-through from money market rate to bank lending rates, Aydın (2007) find that corporate loan rates are not sensitive to changes in the short term policy rates, while consumer (cash, automobile and housing) loan rates are responsive to the policy rate.

After the global crisis when central banks in advanced countries took extraordinary measures and ample global liquidity dominated international financial markets, the banking sector received large external funds at lower costs and easily financed its credit operations. The decreased interest rates and growth prospects in advanced countries encourage international funds searched for a higher yield around the globe and the capital inflows to emerging markets, including Turkey. As massive capital inflows fed into domestic credit and credit volume rapidly expanded, concerns on financial stability increased significantly. Hence, in this period, arguing that the elasticity of demand for bank loans to interest rate was low and higher interest rates might have attracted more capital inflows, the Central Bank of Turkey put additional measures such as reserve requirements other than its main policy tool, short term interest rates, in order to curb the macrofinancial risks and safeguard the financial stability (Kara, 2011).

In sum, on the statistical ground, the nonlinear and linear VAR models are alike. From an economic perspective, both models capture the first round effects, signifying the effects of real sector on financial system. They also provide significant findings on second round effects, the effects of financial system on real sector, to some extent through the interaction term between dummy variable and industrial production. But, as nonlinearity tests suggest, it may be reasonable to consider the interaction between real sector and financial sector through different interest rate regimes by using a nonlinear VAR model under the analysis period, when the inflation regime has prevailed. The short-term interest rate is the main monetary policy tool, which is effectively used after the introduction of inflation targeting regime, and it is effective in determining the cycles both in financial sector and real sector.

It is worth to note that our main aim is not to choose the best VAR model, but find the best performing VAR model in forecasting the macroeconomic and macrofinancial variables since we primarily interested in obtaining forecasted values for macro indicators. The forecast performances of linear and nonlinear VAR models are analyzed in detail in Appendix B.

5.3 Panel Data Models

5.3.1 Data

Monthly panel dataset consists of 12 banks observed over the December 2002-December 2012 period. Twelve banks hold around 86 percent of banking sector total assets. The dependent variable is the ratio of nonperforming loans to total gross loans. The control variables are growth rates of industrial production and total loans, inflation, EMBI, bank leverage, bank profitability, and bank total assets. Bank total assets are subjected to logarithmic transformation. The data sources for macroeconomic variables are the Central Bank of the Republic of Turkey[7], for macrofinancial variables are Banking Regulation and Supervision Authority[8], and for microeconomic variables are the Turkish Banking Association[9].

The Banking Regulation and Supervision Agency defines the nonperforming loans by its regulation on determination of qualifications of loans and other receivables by banks (Banking Regulation and Supervision Agency, 2006). Accordingly regulation classifies loans and other receivables into five categories.

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[7] http://evds.tcmb.gov.tr.

[8] http://ebulten.bddk.org.tr/ABMVC.

[9] http://www.tbb.org.tr/tr/banka-ve-sektor-bilgileri/veri-sorgulama-sistemi/mali-tablolar/71.

(1) Loans of a Standard Nature and Other Receivables. This includes loans and receivables for which payments are made on terms, no repayment problems are not expected in the future and which are totally recoverable / collectable.

(2) Loans and Other Receivables Under Close Monitoring. This includes loans and receivables of which the repayment is highly likely but also the collection of capital and interest payments is delayed for more than thirty days as of the day of their payment dates for several reasons, however which do not carry the condition of delaying time to be classified among Group Three.

(3) Loans and Other Receivables with Limited Recovery. This includes loans and receivables for which it is believed that recovery by banks of principal or interest or both would delay for more than ninety days from their terms or due dates due to reasons such as problems encountered by debtors over operating capital financing or additional liquidity creation.

(4) Loans and Other Receivables with Suspicious Recovery. This includes loans and receivables for which the delay of recovery of principal or interest or both from respective terms or due dates exceeds one hundred eighty days provided that this delay is not longer than one year.

(5) Loans and Other Receivables Having the Nature of Loss. This includes loans and receivables for which recovery of principal or interest or both delays for more than one year from respective terms or due dates.

The regulation stipulates that all the loans classified as Groups Three, Four and Five are considered nonperforming. Therefore, nonperforming loans implies loans and other receivables for which recovery of principal and interest or both delays for more than ninety days from their terms or due dates.

5.3.2 Results of Linear Panel Data Models

5.3.2.1 Results of Fixed Effects and Random Effects Models

During an economic boom, firms' profits increase, asset prices rise and customers' expectations are optimistic. At these times, strong aggregate demand brings about more than proportional growth in bank lending and in the economic agents' indebtedness. However, as economic conditions worsen, firms' profitability and households' disposable income deteriorate and hence borrowers' creditworthiness impair. Also the fall in asset prices depresses the financial wealth of customers and the value of collateral. As the process unravels real levels of nonperforming assets, banks' balance sheets start to deteriorate (Quagliariello, 2006). This process is called cyclicality as the changes in macroeconomic conditions affect financial system.

Hence, the asset quality of banks deteriorates during cyclical downturns requiring banks to raise more capital. However, this is often the period exactly when capital become scarce and its cost is higher than normal times. Facing with higher capital requirements, banks are forced to squeeze the credit supply to the economy considering the difficulties in raising the capital, which in turn resulting in credit contraction that may have systemic implications (Cavallo and Majnoni, 2001). This feedback between real economy and financial system exacerbates the effects of the stress in the economy, which is called procyclicality. In a nutshell, we can argue that cyclicality measures the extent that macroeconomy affects financial system and procyclicality measures the extent of feedback from financial system to real economy through amplifying its fluctuations.

This is especially true if banks have no capital buffer or thin one over minimum capital requirements. Banks' own behavior also plays crucial role in this process since they may be prone to underestimate future losses during economic booms as they relax their lending criteria, have more concentrated loan portfolio and reduce provision for future losses (Pain, 2003). In turn, excessive lending accelerates the deterioration in banks' loan portfolio.

The linear panel data model takes the following form:

$$\log\left(\frac{NPL}{Gross\ Loans}\right)_{it} = \alpha_i + \beta_1 growth\ rate\ of\ industrial\ production_{it}$$

$$+ \beta_2 growth\ rate\ of\ total\ loans_{it} + \beta_3 inflation_{it} + \beta_4 \log(total\ assets)_{it}$$

$$+\beta_5\ overnight\ interest\ rates_{it} + \beta_6 EMBI_{it} + \beta_7 leverege\ ratio_{it} + \beta_8 ROE_{it} + e_{it} \tag{5.2}$$

Since micro series are not immune from breaks and outliers in the data like macroeconomic and macrofinancial series, in parallel to the implementation in VAR modeling we also use dummy variables in panel data modeling. We control for structural breaks only for the global crisis period. Intercept and slope dummy variables are included in the model together or separately. No structural break case is also considered. According to the AIC values, the best model both for fixed effects and random effects panel data modeling is the one that includes both intercept and slope dummy variables for the period 2008:11 -2010:3.

The relevance and expected signs of the relationships between the nonperforming loans and the chosen variables are as follows:

- The dependent variable nonperforming loans are proxy for expected loss by banks. Nonperforming loans are expected to behave procyclically i.e. nonperforming loans tends to increase (decrease) during economic downturns (expansions).
- We measure the economic activity by the industrial production index since a growing economy is likely to be associated with less unemployment, growing incomes and less financial depress. An alternative measure could be GDP growth rate or output gap but since there is no monthly data for these series we necessarily prefer industrial production index as a measure of business cycle. The

expected sign of industrial production index is negative since creditworthiness of banks' customers depends on economic conditions. As economic conditions improve, borrowers' ability to repay loans increases. On the other hand, when growth slows down, cash flows (e.g. wages) to firms and households decreases and this, in turn, makes it difficult for them to pay the interest and principal on bank loans (Salas and Saurina, 2002).

- We expect a negative relationship between credit growth rate and the ratio of nonperforming loans to total loans since the ratio is getting smaller as the loans has grown. Hence, we believe during rapid credit growth periods, banks relax their credit standards as a result of aggressive supply policy of banks. A bank interested in increasing its market share is likely to reduce its borrowers' quality levels. And, hence, such a bank would be negatively affected by adverse selection problem. If the credit expansion is intended in a brand new geographical area or economic sector where bank has no earlier experience, the adverse selection problem would increase (Salas and Saurina, 2002). Another view on the relationship between credit growth and nonperforming loans weighs on demand factors suggesting a negative sign (Quagliariello, 2006).
- Inflation may affect customers' debt servicing capacity through different channels and may signal positive or negative relationship. Higher inflation may make debt servicing easier by reducing real value of outstanding loans. Therefore, the relationship between inflation and nonperforming loans could be negative. However, since higher inflation erodes the customers' capacity to payback their debt by reducing real income or as the Phillips curve implies it is associated with low unemployment (Nkisu, 2011), we can expect positive relationship between inflation and nonperforming loans.

- Rising interest rates is likely to indicate growing financial strains in an economy. Increased interest rates may lead to financial fragility through an increase in the interest service burden for debtors (Arpa, 2001). As higher interest rates affect borrowers' capacity to payback adversely, overnight interest rates are expected to negatively impact asset quality.
- EMBI, which is a proxy for country risk, has a positive relationship with nonperforming loans. Since there is a close relationship between a country's risk profile and its financial system's risk profile, the asset quality may deteriorate due to an increase in country risk
- Total assets of banks is a control variable for bank size.
- As leverage ratio, defined as common equity Tier 1 capital to total assets, declines, bank risk profile deteriorates. In this sense, it is a measure of riskiness that is signified by the potential to create assets per unit of capital. Hence, the relationship between leverage ratio and nonperforming loans is expected to display negative sign since riskier banks may record more losses.
- Bank profitability as it is measured by return on equity and nonperforming loans are expected to display negative relationship. On the other hand, it also may signal banks' incentives for a riskier credit policy and this reflects a positive sign.

The estimation results of fixed and random effects models are given in Table 17.

For fixed effects estimation results, all coefficients are statistically significant. Except industrial production and leverage ratio, the signs of coefficients of all variables are in line with theoretical expectations .The coefficients of intercept dummy variable and the interaction term of industrial production and profitability, ROE, is also statistically significant and their signs are as expected.

Table 17: Estimation Results for Static Panel Data Models (Equation 5.2)		
	Fixed Effects	**Random Effects**
Industrial production	2.1203***	1.6318***
Total loans	-0.4751***	-0.7261***
Inflation	-2.0933**	-2.4423***
Overnight interest rate	0.0086***	-0.0061*
EMBI	0.0008***	-0.1968***
Total assets	-	0.0009***
Leverage ratio	7.0078***	6.8767***
ROE	-0.6962***	-0.6640***
Dummy08-10	1.1273***	0.8273**
Dummy08-10*Ind. Prod.	-2.2947***	-1.7728**
Dummy08-10*Total loans	-1.3493	-1.1297
Dummy08-10*Inflation	6.7172	7.1952*
Dummy08-10*Interest rate	-0.0500	-0.0358
Dummy08-10*EMBI	-0.0005	-0.0006
Dummy08-10*Leverage	1.1729	1.1968
Dummy08-10*ROE	-3.4060***	-3.3608***
df	1281	1292
Sum of squared residuals	233.22	235.59

*,**,*** indicate respectively 10, 5 and 1 percent significance levels.

Unlike the theoretical predictions, industrial production positively affects the nonperforming loans. This may be due to the fact that macroeconomic fluctuations are not quickly transmitted to the nonperforming loans of banks. This finding supports the notion that bank asset quality deteriorates with a lag as industrial production grows due to loosen credit standards applied during boom period (Beck et al, 2013). Although the changes in industrial production have delayed impact on the nonperforming loans, inflation, which is another aspect of macroeconomic activity, seems to be more rapidly transmitted to the asset quality of banks. The coefficient of inflation is negative and statistically significant. Hence, since higher inflation erodes the real value of the outstanding debt for the customers there is a negative relationship between inflation and nonperforming loans.

Rapid credit growth affects the nonperforming loans negatively and significantly. Therefore, banks seeking to expand their loan portfolios too rapidly may face a decline in nonperforming loans ratio as non performing loans get smaller relative to the stock of total loans.

We control for bank size by using banks' total assets. According to the estimation results, relatively big banks are less exposed to problem loans. This may be due to the fact that a big balance sheet allows the bank managers to grant loan in different geographical areas and to different business segments to deal with asymmetric shocks (Salas and Saurina, 2002).

Country profile affects nonperforming loans positively as expected. On the other hand, an increase in bank profitability reduces non-performing loans. While it is statistically significant, leverage ratio displays unexpected sign most probably because of sample covers the period after 2000 crisis when nonperforming loans have continuously decreased while total assets (as a denominator of leverage ratio) have increased significantly.

For the random effects model, all coefficients are statistically significant and, except industrial production, overnight interest rate, EMBI and leverage ratio, the signs of coefficients of all variables are in line with expectations.

When we evaluate the fixed effects model versus random effects model, the Hausman specification test results suggest to use random effects model, i.e. GLS estimator is consistent, although the test does not necessarily lead to a choice between the fixed and random effects models. However, since it is obvious that the sample which makes up the cross sectional units, i.e. banks, is not obtained by some random sampling procedure, then it is more reasonable to use fixed effects models (Erlat, 2008).

5.3.2.2 Results of Dynamic Panel Model

The relation between the nonperforming loans and the business cycle is reestimated in the context of a dynamic model.

The specification takes the following form:

$$\log\left(\frac{NPL}{Gross\ Loans}\right)_{it}$$
$$= \mu_i + \beta_1 \log\left(\frac{NPL}{Gross\ Loans}\right)_{it-1} + \beta_2 growth\ rate\ of\ industrial\ production_{it}$$
$$+ \beta_3 growth\ rate\ of\ total\ loans_{it} + \beta_4 inflation_{\ it} + \beta_5 \log(total\ assets)_{it}$$
$$+\beta_6\ overnight\ interest\ rates_{it} + \beta_7 EMBI_{it} + \beta_8 leverege\ ratio_{it} + \beta_9 ROE_{it} + e_{it} \tag{5.3}$$

Along with the variables used in the static panel data models, the model includes lagged dependent variable. We use the Arellano-Bond (1991) estimator to estimate the model and to compute estimates for dynamic model from panel data.

Pain (2003) argues that the choice between static and dynamic models should ideally be motivated by the economic theory. If nonperforming loans adjust slowly following a default event, then a dynamic model would be more appropriate. Otherwise, if it is more likely that a surprise increase in nonperforming loans in one year is followed by a surprise increase in nonperforming loans in the next year, then a static panel data model would be more appropriate. Actually being compliant with the accounting rules, banks recognize the full amount of any probable loss as soon as the default event realizes, which argues in favor of static model (Pain, 2003). Since there is no well-articulated theory about the dynamic adjustment of nonperforming loans, it is not crystal clear which theory should be preferred over the other. Then it is reasonable to present the results of both of them.

Since the number of instruments can be very high when using the Arellano-Bond estimator, we allow up to 2 lags of the instrumented variables considering the sample size and hence degrees of freedom.

The null hypothesis of the Arellano – Bond test for autocorrelation is no autocorrelation and should be applied to the differenced residuals. The null hypothesis that there is no autocorrelation cannot be rejected at 5 percent significance level. The Sargan test of overidentifying restrictions implies that the instruments are appropriate (Table 18).

We evaluate possible structural breaks and outliers in panel data modeling parallel to the implementation in VAR modeling. We control for structural breaks only for the global crisis period. Intercept and slope dummy variables are included in the model together or separately. No structural break case is also considered. According to the AIC values, the best model both for dynamic panel data modeling is the one that includes only intercept dummy variable for the period 2008:11 - 2010:3.

The estimation results of dynamic panel model are presented in Table 18.

Considering the fact that nonperforming loans are not immediately written down, the ratio of nonperforming loans of one period is in close relation with that of the previous period. In other words, there is a strong persistence in nonperforming loans. The one-month lagged dependent variable is significant and the persistence of nonperforming loans is relatively high.

Except inflation and leverage ratio, all coefficients are statistically significant and both macroeconomic variables and bank specific variables contribute to the build-up of nonperforming loans. Except overnight interest rate, the sign of coefficients of all variables are in line with expectations.

Table 18: Dynamic Panel Estimation Results (Equation 5.3)	
	Dependent variable: NPL Ratio
Lagged NPL Ratio	0.8681***
Industrial Production	-0.1962***
Total Loans	-0.2165***
Inflation	0.0963
Overnight Int. Rate	-0.0048***
Total assets	-0.0783***
EMBI	0.0001*
Leverage Ratio	0.2358
ROE	-0.1200*
Dummy08-10	0.0264***
df	1296
Sum of squared residuals	13.44
Arellano-Bond test	0.1379 (p value)
Sargan test	0.1338 (p value)

*,**,*** indicate respectively 10, 5 and 1 percent significance levels.

As we mentioned before, the higher inflation may erode the debt servicing capacity of bank customers to payback their debt by reducing real income and hence its coefficients may take positive sign. Being different from static panel estimation results, the coefficient of industrial production index is negative and statistically significant.

5.3.3 Results of Nonlinear Panel Data Model

As we did in VAR modelling, in panel data framework, we consider possible nonlinearities in macroeconomic and macrofinancial variables in line with the findings from earlier studies in literature. To do this, we employ a nonlinear panel data model as it is discussed in subsection 4.3.2.

We estimate the following two regime threshold panel data model:

$$\begin{aligned}\log\left(\frac{NPL}{Gross\ Loans}\right)_{it} &= (\alpha_i + \beta_1 growth\ rate\ of\ industrial\ production_{it} \\ &+ \beta_2 growth\ rate\ of\ total\ loans_{it} + \beta_3 inflation_{it} \\ &+ \beta_4 \log(total\ assets)_{it} + \beta_5\ overnight\ interest\ rates_{it} \\ &+ \beta_6 EMBI_{it} + \beta_7 leverege\ ratio_{it} + \beta_8 ROE_{it})\ I(q_{it} \le \gamma) \\ &+ (\alpha_i + \beta_1 growth\ rate\ of\ industrial\ production_{it} \\ &+ \beta_2 growth\ rate\ of\ total\ loans_{it} + \beta_3 inflation_{it} \\ &+ \beta_4 \log(total\ assets)_{it} + \beta_5\ overnight\ interest\ rates_{it} \\ &+ \beta_6 EMBI_{it} + \beta_7 leverege\ ratio_{it} + \beta_8 ROE_{it})\ I(q_{it} > \gamma) + e_{it}\end{aligned} \quad \textbf{(5.4)}$$

According to test results, we strongly reject the null hypothesis of linearity as it is given in Table 19. We find that the best transition variable is profitability, i.e. ROE. The second best transition variable is overnight interest rate.

On the other hand, we prefer to choose overnight interest rate as a transition variable instead of ROE. First, ROE is a bank specific variable, which indicates mainly the future health of bank and its ability to construct buffer against unfavorable shocks. Second, interest rates is the main monetary policy tool, which is effectively used after the introduction of inflation targeting regime, and it is effective in determining the cycles both in financial sector and real sector.

Table 19: Test for Threshold Effects		
Variable	**F statistic**	**p-value**
ROE	270.02	0.0000
Overnight interest rate	166.40	0.0000
Total Loans	155.78	0.0000
Industrial production	125.98	0.0000
Inflation	124.69	0.0000
Leverage ratio	46.28	0.0000
EMBI	8.16	0.0000

In line with the obtained results from linear VAR modeling, we control for structural breaks only for the global crisis period. Intercept and slope dummy variables are included in the model together or separately. No structural break case is also considered. According to the AIC values, the best nonlinear panel data model is the one that includes both intercept and slope dummy variables for the period 2008:11 -2010:3.

We obtain two different estimation results depending on regime-dependent coefficients: One for high interest rate regime, i.e. when overnight interest rate is above the estimated threshold value and the other one is low interest rate regime. Given the delay parameter is 2, we obtain the optimal threshold value for the overnight interest rate, which is 12 percent.

After the transition variable is specified and the threshold value is determined, we estimate a piecewise linear model for two regimes. Table 20 presents the estimation results for both regimes.

Table 20: Estimation Results for Nonlinear Panel Data Model		
	Low Regime	**High Regime**
Industrial production	2.3922***	1.1064***
Total loans	-0.5624***	-0.1360
Inflation	1.5107***	-2.5122**
Overnight interest rate	-0.0166***	0.0323***
Total assets	-0.2135***	-0.0488
EMBI	-0.0005***	0.0006***
Leverage ratio	4.2583***	2.3111***
ROE	-0.8017***	-0.3848***
Dummy08-10	0.4175	1.5871**
Dummy08-10*Ind. Prod.	-2.3965**	-1.1537
Dummy08-10*Total loans	-1.0826	0.1146
Dummy08-10*Inflation	1.1567	2.4682
Dummy08-10*Int. rate	-0.0037	-0.1247**
Dummy08-10*EMBI	0.0008	0.0003
Dummy08-10*Leverage	-2.1170**	9.6333***
Dummy08-10*ROE	-0.3393	-4.5451***
No of obs	500	752
Sum of squared residuals	10.76	94.25

*,**,*** indicate respectively 10, 5 and 1 percent significance levels.

Under low regime, i.e. below the threshold, the coefficients of all variables are statistically significant. Under high regime, except total loans and total assets, all coefficients are statistically significant. Unlike linear static and dynamic panel data estimation results, one remarkable finding from the nonlinear panel data is that the sign of the coefficient of the overnight interest rate is statistically significant. Considering that the threshold value is 12 percent, the high regime roughly covers the period up to the beginning of the global crisis. Therefore, a nonlinear modeling structure allows us to capture the interest rate effect thoroughly. But the size of the effect is small to some extent, indicating the importance of the structural factors, which were dominantly in play at that period starting after the 2001 economic program.

5.4 Forecasting and Stress Testing

We form an analysis to evaluate the effects of exogenous shocks on banks' nonperforming loan performance, which constitutes a sensitivity analysis. Accordingly, for the sampling period 2002:12-2011:12, we estimate the nonlinear VAR model and obtained the estimated elasticities for three macroeconomic variables and one macrofinancial variable, namely industrial production growth rate, inflation, overnight interest rates and credit growth rate. As a next step, we forecast[10] these variables' values for the year 2012, which provides us 12 monthly forecasted values. We employ the forecast equation 4.62 in Chapter 4.4.

The correlation coefficients between the forecasts from the linear and nonlinear models for industrial production growth rate, inflation, overnight interest rates and credit growth rate are high and close to 1, except overnight interest rate.

For other macroeconomic variables and bank specific variables, we calculated the historical rate of change for these variables and use the average of these changes as a rate of growth in these variables for the year 2012. Accordingly, we use an annual growth rate of 10 percent for total assets and we assume that bank leverage and profitability remain same. We also use an almost 1 percent change in EMBI for 2012.

Then, after obtaining the forecasted value for the macroeconomic, macrofinancial and bank specific determinants of banks' asset quality, through

[10] Considering the outliers and structural breaks in the data, its erratic structure and the short length of time period of this study, it is rather difficult to obtain accurate nonlinear forecast values for the macro indicators.

using estimated elasticities, we calculate the nonperforming loans for year 2012. These elasticities are obtained from linear fixed effects, random effects, dynamic fixed effects and nonlinear fixed effects models. The calculated nonperforming loans figures by these models and forecast evaluation criteria are given by Table 21.

Table 21: Forecasting Results for Log(NPL Ratio)
(Estimation period: 2002:12-2011:12)

	Linear Fixed Effects	**Random Effects**	**Dynamic Panel**	**Nonlinear Fixed Effects**	**Actual Values**
2012:01	0.2763	-1.0101	-1.8623	-1.2821	-1.5578
2012:02	0.2791	-1.0009	-1.6815	-1.3032	-1.5557
2012:03	0.2919	-0.9854	-1.5267	-1.3135	-1.5611
2012:04	0.3136	-0.9728	-1.3964	-1.2869	-1.5633
2012:05	0.3164	-0.9669	-1.2800	-1.3069	-1.5681
2012:06	0.3384	-0.9540	-1.1832	-1.2830	-1.5755
2012:07	0.3469	-0.9517	-1.0990	-1.2749	-1.5655
2012:08	0.3400	-0.9539	-1.0226	-1.3057	-1.5533
2012:09	0.3459	-0.9470	-0.9577	-1.3196	-1.5305
2012:10	0.3572	-0.9367	-0.9024	-1.3252	-1.5283
2012:11	0.3702	-0.9259	-0.8551	-1.3265	-1.5264
2012:12	0.3786	-0.9202	-0.8143	-1.3274	-1.5435
RMSE	3.5425	0.3509	0.2147	0.0624	
MAPE	121.2415	38.1342	26.4460	15.9468	
Correlation	0.5225	0.5317	0.5558	0.7855	1.0000

After forecasts for the nonperforming loans were made for the year 2012, they were compared across the above mentioned models through RMSE and MAPE criteria. Accordingly, nonlinear fixed effects model is the best performing model in forecasting the nonperforming loans. Also, when we checked the correlation between the actual and the forecasted values, we observe that the correlation coefficient reaches its highest level for the nonlinear fixed effects panel data model.

In order to test the vulnerability of the financial system to external shocks, we construct scenarios from the VAR model. Scenarios can be composed of shocks to one or several macroeconomic and macrofinancial variables, which are severe enough but plausible. When scenarios are produced from a VAR model, it is also possible to consider the interaction between macro variables in these scenarios, i.e. first and second round effects. On the other hand, in sensitivity analysis, it is only possible to measure the vulnerability of the financial system to one single risk factor given no changes in other variables. Another possible method is to construct the scenarios in line with the forecasts of national or international institutions. For example, International Monetary Fund's (IMF) World Economic Outlook constitutes a beneficial resource in this regard. In this approach, IMF forecasts for macroeconomic variables are considered as baseline scenarios and severe deviations from these forecasts are evaluated as adverse scenarios. Other possible approach to construct scenarios is to replicate historical events that the financial system faced in the past. Again, in this case, since no macro model is employed only possible analysis method is to apply sensitivity analysis.

Here we apply two alternative scenarios in which one scenario represents a severe shock to industrial production and the other one represents a sudden stop in credit growth. Accordingly in the first scenario, it is assumed a 20 percent annual decline in industrial production in nominal terms in the next period (i.e. next month). This is consistent with the decline that occurred in industrial production in the year 2009 with the global financial crisis. Given this decline, we also calculate the corresponding values for other macro variables. Next, using the calculated elasticities from the panel data model we measure the change in nonperforming loans of the banking sector. It also possible to evaluate the resilience of the banking sector to such shocks by observing the change in capital adequacy ratio (CAR) of the sector and checking whether the CAR still continue to remain above the legal minimum (12 percent).

Against a shock due to a severe decline in industrial production, the nonperforming loans ratio of the sector increases from 2.7 percent to 4.30 percent. This amounts to 59 percent increase in nonperforming loans ratio, which is bigger than the increase of almost 33 percent in the ratio in 2009 due to a decrease of 23 percent in industrial production. The response of nonperforming loans to the industrial production is given in Figure 13. The corresponding change in the capital adequacy ratio of the banking sector is given in Figure 14. The capital adequacy ratio declines from 16.5 percent to around 15.6 percent.

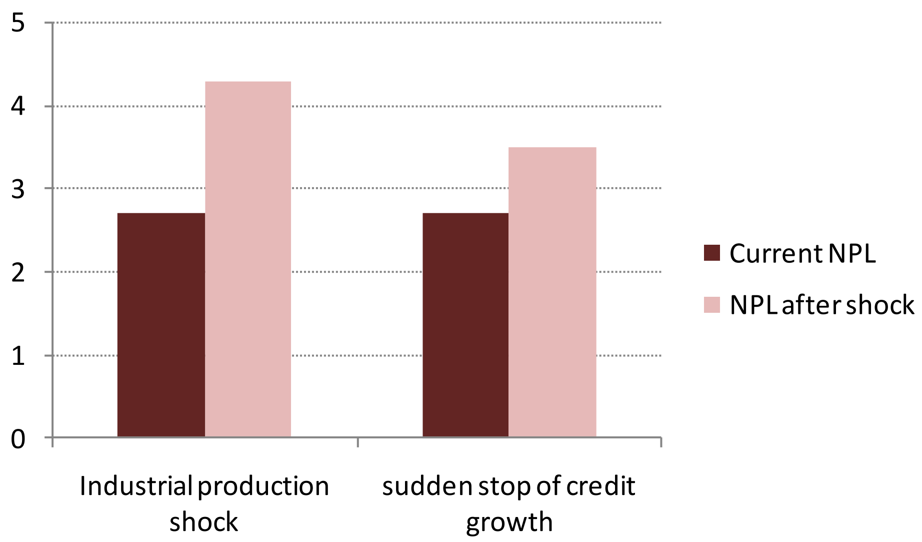

Figure 13: The response of the nonperforming loans to the shocks (%)

The other scenario represents the sudden stop of the credit growth, which is a less severe shock compared to the industrial production shock. Hence we assume the annual credit growth rate declines to zero in the next period from the level of 16 percent. Due to this shock, the nonperforming loans increase from 2.7 percent to 3.5 percent. And the capital adequacy ratio declines from 16.5 percent to 16.1 percent.

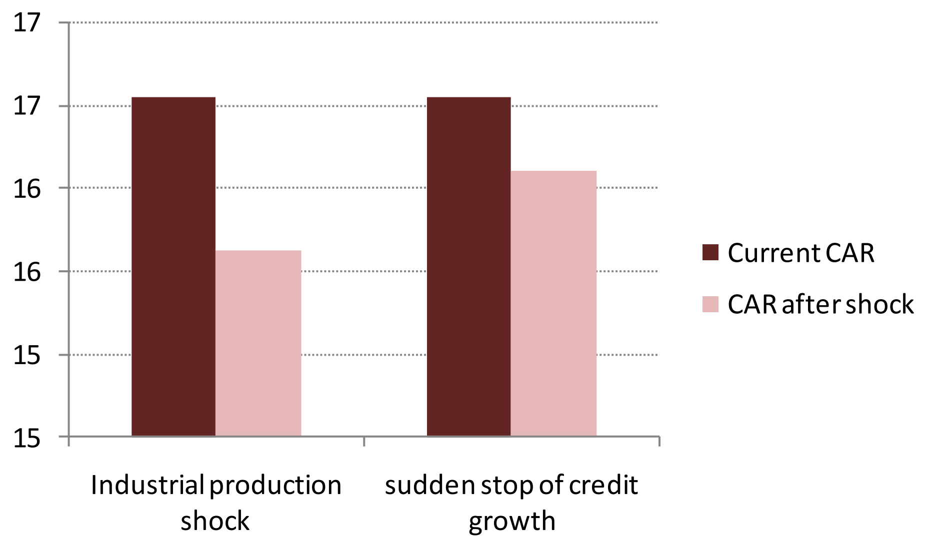

Figure 14: The response of the capital adequacy ratio to the shocks (%)

5.5 Concluding Remarks

In this section, we first examine the relationship between macroeconomic and macrofinancial variables in order to reveal the interaction between the real sector and the financial system. Accordingly, we find significant evidence for first round effects, which works from the real sector through the financial system. Also, there is some evidence for the second round effects (feedback effects) from financial system to the real side of the economy. The major expectation from the macro model that is operationalized with a VAR specification is to produce macro scenarios which then is used to measure effects of macro shocks on banks' asset quality.

In order to find the determinants of the asset quality of the banking sector, we employ panel data models. These models cover a range models depending on whether it is static or not and whether it is linear or nonlinear. We find that bank specific variables, and macroeconomic and macrofinancial variables are statistically significant in determining nonperforming loans. The macroeconomic and macrofinancial variables overlap with those employed in the VAR model, which pave the way for constructing scenarios from the VAR model.

We also try to stress nonperforming loans by using macroeconomic shocks produced from the VAR model. To do this, we forecast macrofinancial and macroeconomic variables by using VAR model. Then, after obtaining the forecasted value for the macroeconomic, macrofinancial and bank specific determinants of banks’ asset quality, through using estimated elasticities, we calculate the nonperforming loans for year 2012. These elasticities are obtained from linear fixed effects, random effects, dynamic fixed effects and nonlinear fixed effects models. We observe that nonlinear fixed effects panel data model perform well in forecasting nonperforming loans.

We also use two alternative scenarios to test resilience of the banking sector. In the first scenario, a shock to industrial production (20 percent drop in nominal terms) is considered, and the second scenario represents a sudden stop in credit growth. We calculated the deterioration in the asset quality proxied by the nonperforming loans and change in capital adequacy ratios. Accordingly, we found that the banking sector is resilient such shocks.

CHAPTER 6

CONCLUSION

The experiences acquired from the recent global crisis have emphasized the importance of systemic risk and highlighted the futility of efforts for simply expanding the coverage of current regulation framework to mitigate riskiness accumulated in the financial system. Monitoring, assessing and mitigating systemic risk require macroprudential tools and measures. Procylicality and interconnectedness in the financial system, constituting the time and cross sectional dimension of systemic risk respectively, necessitate to adopt not only a system wide approach covering the interlinkages between financial system and real economy, but also a more granular method to analyze individual financial institution specific properties and developments.

In order to measure both the extent which the macroeconomy affects banking sector (cyclicality) and in turn, the banks' reaction to changing macroeconomic conditions further influences the macroeconomy and amplifies its fluctuations (procyclicality), central banks and international institutions in practice rely on macro stress testing framework. Macro stress tests essentially test the resilience of banking sectors under weak macroeconomic conditions. Hence, macro stress tests provide policy makers with information on potential losses of financial system under extraordinary but plausible scenarios.

In literature, one stream of applied studies adopts a VAR framework in testing the vulnerability of the banking sector to external shocks. Considering the fact that the balance sheet of the banking sector tends to move in parallel to economic cycles, VAR models may provide efficient and reliable estimates in considering the interaction between macroeconomic and macrofinancial variables. In line with the increased interest in the relationship between banking system and economic cycles, more and more effort put into modeling of this relationship to quantify the elasticities and size feedbacks from one to another. Whereas the VAR model focuses on the interaction between macroeconomic and macrofinancial variables and measuring the size of feedbacks from financial system to real economy, by a panel data model it is possible to analyze the risk profile of the banking sector by employing both macro and bank specific indicators. In literature, various studies are held in order to understand the relationship between asset quality, which is proxied by nonperforming loans or loan loss provisions, and business cycles.

After the global crisis, increased interest in systemic risk has encouraged researchers to develop more sophisticated and compact approaches to macro stress testing. Based on a framework of a suite-of-models, these studies (for example, Alessandri et al. 2008; Aikman et al., 2009; Andersen et al., 2008) combine a macro model, mostly a VAR model to be used to construct scenarios, with micro models, which are to be employed to estimate major banking risks, such as credit risk.

Another striking feature of the macro stress testing studies is that they are unexceptionally based on the strict assumption of linearity, although major macroeconomic and macrofinancial variables inherently reflect nonlinearities to some extent. Many macroeconomic variables behave asymmetrically over different phase of business cycles, called cyclical asymmetry, and hence exhibit nonlinear dynamics (Neftçi, 1984; Hamilton, 1989; Sichel, 1993; Terasvirta and Anderson, 1992 and Öcal and Osborne, 2000). Hence, it is well documented that during an economic crisis macroeconomic variables decline sharply, but during upswings they do not recover at that pace.

Becoming popular especially after the recent global crisis, it is also documented that the financial system shows nonlinear dynamics to some extent since it is exposed to risk spillovers and negative externalities largely due to the interlinkages within the financial system. One institution may impose negative externalities on other institutions and on the whole system (Adrian and Brunnermeier, 2011). Or the failure of a bank may produce a spillover effect in the system leading to negative externalities through the interlinkages among banks in interbank market or in payments and settlements system or by inducing an imperfect depositor migration (Acharya, 2009). Therefore, as it is evident from the last global crisis, the transition of a financial system from a sound state to a distressed state could happen in a nonlinear fashion.

Hence, there is sufficient evidence on the nonlinear characteristic of macroeconomic time series and the studies produced especially after the global crisis have drawn attention to possible nonlinearities inherent in the financial system. However, existing stress testing studies neglect nonlinear data generating mechanisms. This may lead inefficient estimation results and also their reliability may be questionable. Therefore, earlier literature suffers from the unfavorable consequences of building its setup on a strict assumption of linearity and the usefulness of these studies is questionable to some extent.

By this thesis, we aim to make several contributions to the literature. First, although there are studies inquiring the nonlinear features of macroeconomic and macrofinancial time series, this is the first study that employ nonlinear econometric methods in an integrated way in macro stress testing the banking sector. Second, as we discuss in detail in the second chapter, in literature macro stress studies either adopt VAR or panel data approach except few recent studies combining both techniques. Considering the existing stress testing studies in Turkey, this is the first time that VAR and panel data models are combined to analyze the resilience of the Turkish banking sector. Considering its compactness by combining macro and micro models, the adopted framework allows granularity through evaluating the credit risk based on bank-level data and its focus on the interaction between business and financial cycles, including both first and second round effects. Third, in addition to this combined approach, by this thesis, this is the first time that both VAR and panel data models are structured in nonlinear fashion.

Taking these findings into consideration, in order to conduct a macro stress test of credit risk, the thesis presents a suite of models, which are a set of independent but complementary models.

We employ both linear and nonlinear VAR models to forecast the future values of macroeconomic and macrofinancial variables, namely industrial production, consumer price index, interbank overnight deposit rate and banking sector total loans. Then, we use these forecasted values, which are obtained from the linear and nonlinear VAR models, in the panel data models to predict future values of the nonperforming loans of the banks, which is a proxy variable for the credit risk of banks. These elasticities are obtained from linear fixed effects, random effects, dynamic fixed effects and nonlinear fixed effects models. By comparing the predicted values and the actual values of the nonperforming loans, we can evaluate which panel data model delivers superior prediction performance for credit risk by employing several measures such as root mean square error, mean absolute percentage error and vice versa.

Such an approach also allows us to conclude which VAR model produces more precise forecasted values and whether a linear or a nonlinear VAR model structure should be adopted. Hence, we make a decision between linear and nonlinear VAR models based on an evaluation about their performance in producing good forecast values. Therefore, it is worth to note that our main aim is not to choose the best VAR model, but find the best performing VAR model in forecasting the macroeconomic and macrofinancial variables since we primarily interested in obtaining forecasted values for macro indicators.

The results of the VAR model suggest some evidence for first round effects, which works from the real sector through the financial system. Also, there is some evidence for the second round effects (feedback effects) from financial system to the real side of the economy. We consider nonlinear dynamics in macroeconomic and macrofinancial variables as regime changes in overnight interest rates. The panel data models perform well in explaining the determinants of asset quality of banks. The empirical results suggest there is significant interaction between macro indicators. And several macroeconomic and bank specific variables are good indicators in explaining developments in asset quality of banks. In the nonlinear fixed effects panel data model, as in the nonlinear VAR model, we find overnight interest rates the most reasonable transition variable.

The empirical results show that nonlinear VAR and nonlinear panel data models provide better results, which proves our cautious approach on modelling right. This is also especially important that since earlier literature on macro stress testing ignores the nonlinear data generating mechanism, those studies may suffer from incompetence of providing reliable and accurate estimates and outcomes.

The major expectation from the macro model that is operationalized with a VAR specification is to produce macro scenarios which then is used to measure effects of macro shocks on banks' asset quality. We try to stress nonperforming loans by using macroeconomic shocks produced from the VAR model. To do this, we forecast macrofinancial and macroeconomic variables by using VAR model. Then, after obtaining the forecasted value for the macroeconomic, macrofinancial and bank specific determinants of banks' asset quality, through using estimated elasticities up to the year 2011, we calculate the nonperforming loans for year 2012. These elasticities are obtained from linear fixed effects, random effects, dynamic fixed effects and nonlinear fixed effects models. We observe that nonlinear fixed effects panel data model perform well in forecasting nonperforming loans.

We use two alternative scenarios to test resilience of the banking sector. In the first scenario, a shock to industrial production (20 percent drop in nominal terms) is considered, and the second scenario represents a sudden stop in credit growth. We calculate the deterioration in the asset quality proxied by the nonperforming loans and change in capital adequacy ratios. Accordingly, we find that the banking sector is resilient to such shocks.

In a nutshell, this thesis is the first study adopting a nonlinear method in macro stress testing analysis in an integrated way. It should be noticed that macroeconomic and macrofinancial variables may exhibit nonlinearities, and the interaction between the real economy and the banking sector may have nonlinear characteristics. The recent global crisis has showed the significant role of systemic risk factors, including aforementioned nonlinearities, in building-up of risks and turning it into a full-fledged crisis if triggering factors are in place.

As the recent global crisis has emphasized, financial stability challenges exhibit a systemic characteristic as institutions and markets are interlinked to each other. Also, financial crises of a systemic nature may severely damage economies and financial systems, and result in significant costs to public finance and also to social life and business environment. This necessitates timely adopted, proactive measures by policy makers, decisions of which should be based on a full-fledged framework for analyzing, detecting and mitigating the systemic risk. Being part of such a framework, macro stress tests should employ nonlinear models in order to ensure that proper and timely macroprudential measures in place to safeguard the financial stability.

Before concluding, it should be mentioned that this thesis is not immune from some limitations, and to complement it, some further work can be suggested. About the limitations, the analyses carried out in this thesis are based on a time period of relatively short length and the data set is subject to several possible outliers and structural breaks. Hence, such limitations are the main obstacles to derive more efficient results. Also, to develop and augment the proposed framework in this thesis, other main banking risks such as liquidity risk can be considered and modeled as a further work. To increase the granularity of the proposed work, the credit risk proxied by nonperforming loans can be decomposed to its main elements like consumer loans and corporate loans in order to improve the quality and precision of the analyses focusing on the resilience of the banking sector.

REFERENCES

Acharya, V. V. (2009). A theory of systemic risk and design of prudential bank regulation. *Journal of Financial Stability*, 5(3), 224-255.

Adrian, T. and Brunnermeier, M. K., (2011). CoVaR. *NBER Working Paper,* No. w17454.

Aikman, D., Alessandri, P., Eklund, B., Gai, P., Kapadia, S., Martin, E., … Willison, M. (2009). Funding Liquidity Risk in a Quantitative Model of Systemic Stability. *Bank of England Working Paper,* No.372.

Akyüz, Y and Boratav, K. (2003). The making of the Turkish financial crisis. *World Development*, 31(9), 1549–1566.

Akyüz, Y. (2007). Global rules and markets: Constraints over policy autonomy in developing countries. Retrieved from http://www.bagimsizsosyalbilimciler.org/Yazilar_Uye/AkyuzHaz07.pdf.

Alessandri, P., Gai, P., Kapadia, S., Mora, N. and Puhr, C. (2008). A Framework for Quantifying Systemic Stability. Retrieved from http://qed.econ.queensu.ca/pub/faculty/milne/872/Gai%20FrameworkforQuantifyingSystemicStability.pdf.

Alessandri, P., Gai, P., Kapadia, S., Mora, N. and Puhr, C. (2009). Towards a framework for quantifying systemic stability. *International Journal of Central Banking*, 5, 47-81.

Andersen, H., Berge, T. O., Bernhardsen, E., Lindquist, K. and Vatne, B. H. (2008). A suite-of-models approach to stress-testing financial stability. *Norges Bank Staff Memo 2008/2*.

Anderson, T. W. and Hsiao, C. (1982). "Formulation and estimation of dynamic models using panel data. *Journal of Econometrics*, 18, 47-82.

Arellano, M. and Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *The Review of Economic Studies*, 58, 277 – 297.

Arpa, Markus, Giulini, I., Ittner, A. and Pauer, F. (2001). The influence of macroeconomic developments on Austrian banks: Implications for banking supervision. *Bank of International Settlements (BIS) Papers*, No. 1, 91-116.

Atiyas, İ. and Ersel, H. (2010). Financial markets, regulation and financial crises. In Scherzberg, Arno and Doğan, İlyas and Can, Osman (eds.), Staatliche Finanzmarktregulierung und Eigentumsschutz. Berlin: LIT Verlag Berlin.

Avouyi-Dovi, S., Bardos, M., Jardet, C., Kendaoui, L. and Avouyi-Dovi, J. M. (2009). Macro stress testing with a macroeconomic credit risk model: Application to the French manufacturing sector. *Banque de France Working Paper,* No. 238.

Aydın, H.İ. (2007). Interest rate pass-through in Turkey. *Central Bank of the Republic of Turkey Research and Monetary Policy Department Working Paper*, No. 07/05.

Aysan, A. F., Öztürk, H., Polat, A. Y. and Saltoğlu, B. (2014). *Macro stress-testing approach of credit risk: Turkish case*. Paper presented at 2nd International Conference on Debt Crises and Financial Stability: Global Issues and Euro-Mediterranean Perspectives LEAD, Toulon University, France / GRM, Toulon University, France CES, Kirklareli University, Turkey.

Bai, J. and Perron, P. (2003). Computation and analysis of multiple structural change models. *Journal of Applied Econometrics*, 18(1), 1-22.

Baltagi, B. H. (2001). Econometric analysis of panel data. Chichester: John Wiley and Sons.

Bank for International Settlements (2008). Addressing financial system procyclicality: A possible framework. Note for the FSF Working Group on Market and Institutional Resilience. Retrieved from http://www.financialstabilityboard.org/publications/r_0904e.pdf.

Bank for International Settlements Basel Committee on Banking Supervision (2011). Basel III: A global regulatory framework for more resilient banks and banking systems. Retrieved from http://www.bis.org/publ/bcbs189.pdf.

Banking Regulation and Supervision Agency (2001). Banking Re-Structuring Program.

Banking Regulation and Supervision Agency (2006). Regulation on procedures and principles for determination of qualifications of loans and other receivables by banks and provisions to be set aside.

Banking Regulation and Supervision Agency (2010). *From Crisis to Financial Stability (Turkey Experience).* Banking Regulation and Supervision Agency Working Paper (Revised Third Edition).

Bouvatier, V. and Lepetit, L. (2008). Banks' procyclical behavior: Does provisioning matter? *Journal of International Financial Markets, Institutions and Money*, 18(5), 513-526.

Bouvatier, V. and Lepetit, L. (2010). Effects of loan loss provisions on growth in bank lending: Some international comparisons. Retrieved from http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1663580.

Beck, Roland, Jakubik, P. and Piloiu, A. (2013). Non-performing loans: What matters in addition to the economic cycle?. *European Central Bank Working Papers,* No. 1515.

Becker, Ralf, Osborn, D. R. and Yıldırım, D. (2010). A threshold cointegration analysis of interest rate passthrough to UK mortgage rates. *The University of Manchester Centre for Growth and Business Cycle Research Discussion Paper Series*, No. 141.

Beşe, E. (2007). *Finansal sistem stress testi uygulamaları ve Türkiye örneği*. (Promotion thesis, the Central Bank of the Republic of Turkey, Ankara). Retrieved from http://www.tcmb.gov.tr/kutuphane/TURKCE/tezler/evrimbese.pdf.

Bikker, J. A. and Hu, H. (2002). Cyclical patterns in profits, provisioning and lending of banks. *Netherlands Central Bank DNB Staff Reports*, No.86.

Bikker, J. A. and Metzemakers, P. A. J. (2002). Bank provisioning behaviour and procyclicality. *Netherlands Central Bank Research Series*, No. 50.

Boratav, K., Türel, O. and Yeldan, E. (1996). Dilemmas of structural adjustment and environmental policies under instability: Post-1980 Turkey. *World Development*, 24(2), 373-393.

Borio, C. (2011). Implementing a macroprudential framework: Blending boldness and realism. *Capitalism and Society*, 6(1), Article 4.

Boucinha, M. (2008). The Determinants of Portuguese banks' capital buffers. *Banco de Portugal Working Papers*, No. 1/2008.

Cameron, A. C. and Trivedi, P. K. (2005). *Microeconometrics: Methods and applications.* New York: Cambridge University Press.

Çanakçı, D. (2008). Implications of macro stress testing for financial stability: The case of Turkey. doi: 10.2139/ssrn.1157499.

Cavallo, M. and Majnoni, G. (2001). Do Banks Provision for Bad Loans in Good Times? Empirical Evidence and Policy Implications. World Bank Policy Research Working Papers, No. 2619.

Chan, K.S. (1993). Consistency and limiting distribution of the least squares estimator of a threshold autoregressive model. *Annals of Statistics*, 21, 520-533.

Craig, R. S., Davis, E. P. and Pascual, A. G. (2006). Sources of pro-cyclicality in East Asian financial systems. *Brunel University Economics and Finance Discussion Papers*, No. 06-02.

Central Bank of the Republic of Turkey (2003). *Annual Report 2003*. Retrieved from http://www.tcmb.gov.tr/research/yillik/03ing/yringxyeni.php.

Central Bank of the Republic of Turkey (2005). *Financial stability report*. No.1. Retrieved from http://www.tcmb.gov.tr/yeni/evds/yayin/finist/finisteng.html.

Central Bank of the Republic of Turkey (2006a). *Inflation report*. No.2006/1. Retrieved from http://www.tcmb.gov.tr/research/parapoli/inflation2006I.pdf.

Central Bank of the Republic of Turkey (2006b). *Financial stability report*. No. 3. Retrieved from http://www.tcmb.gov.tr/yeni/evds/yayin/finist/finistv3eng.html.

Central Bank of the Republic of Turkey (2008a). *Annual Report 2008*. Retrieved from http://www.tcmb.gov.tr/research/yillik/08ing/08ing.php.

Central Bank of the Republic of Turkey (2008b). *Financial stability report*. No. 8. Retrieved from http://www.tcmb.gov.tr/yeni/evds/yayin/finist/finistv8eng.php.

Central Bank of the Republic of Turkey (2009). *Financial stability report*. No9. Retrieved from http://www.tcmb.gov.tr/yeni/evds/yayin/finist/finistv9eng.php.

Central Bank of the Republic of Turkey (2010). *Financial stability report*. No. 10. Retrieved from http://www.tcmb.gov.tr/yeni/evds/yayin/finist/finistv10eng.php

Central Bank of the Republic of Turkey (2011). *Financial stability report*. No. 12. Retrieved from http://www.tcmb.gov.tr/yeni/evds/yayin/finist/finistv12eng.php

Davis, E. P. and Zhu, H. (2005). Commercial property prices and bank performance. *BIS Working Papers*, No 175.

De Graeve, F., Kick, T. and Koetter, M. (2008). Monetary policy and bank distress: An integrated micro-macro approach. *Deutsche Bundesbank Discussion Paper Series 2: Banking and Financial Studies*, No. 2008/03

Dovern, J., Meier, C.-P. and Vilsmeier, J. (2010). How resilient is the German banking system to macroeconomic shocks? *Journal of Banking and Finance*, 34, 1839–1848.

Ersel, H. (2013). Politico-economic development of Turkey and the transformation of political Islam. *The Economic Research Forum Working Paper Series, No. 746.*

Ersel, H. (1991). Structural adjustment: Turkey (1980-1990). *Central Bank of the Republic of Turkey Discussion Papers, No. 9107.*

Erlat, H. (2008). *Panel data: A selective survey: Course notes*. Ankara: Middle East Technical Univeristy.

Espinoza, R. and Prasad, A. (2010). Nonperforming loans in the GCC banking system and their macroeconomic effects. *IMF Working Paper*, No. 10/224.

European Commission (2009). *De Larosière Report*. Retrieved from http://ec.europa.eu/internal_market/finances/docs/de_larosiere_report_en.pdf

Foglia, A. (2008). Stress testing credit risk: A survey of authorities' approaches. *International Journal of Central Banking*, 5, 9-45.

Gambera, M. (2000). Simple forecasts of bank loan quality in the business cycle. *Federal Reserve Bank of Chicago Supervision and Regulation Department Emerging Issues Series*, No. 2000/3.

Galvao, A. B. C. (2003). Multivariate threshold models: TVARs and TVECMs. *Brazilian Review of Econometrics*, 23(1), 143-171.

Girault, M. A. G. (2008). *Modeling extreme but plausible losses for credit risk (Technical report)*. Retrieved from Central Bank of Argentina publications website: www.bcra.gov.ar/pdfs/invest/Stress_Test_BCRA.pdf

Glen, J. and Mondragón-Vélez, C. (2011). Business cycle effects on commercial bank loan portfolio performance in developing economies. *Review of Development Finance*, 1(2), 150–165.

Greenlaw, D., Kashyap, A. K., Schoenholtz, K. L. and Shin, H. S. (2012). Stressed out: Macroprudential principles for stress testing. *Chicago Booth Research Paper,* No. 12-08.

Hamilton, J. D. (1989). A new approach to the economic analysis of nonstationary time series and the business cycle. *Econometrica*, 57(2), 357-384.

Hamilton, J. D. (1994). *Time series analysis.* New Jersey: Princeton University Press.

Hansen, B. E. (1996a). Sample splitting and threshold estimation. *Boston College Department of Economics Working Papers*, No. 319.

Hansen, B. E. (1996b). Inference when a nuisance parameter is not identifed under the null hypothesis. *Econometrica*, 64, 413-430.

Hansen, B. E. (1999). Threshold effects in non-dynamic panels: Estimation, testing and inference. *Journal of Econometrics*, 93, 345–368.

Hauner, D. (2009). Public debt and financial development. *Journal of Development Economics*, 88, 171-183.

Huang, X., Zhou, H. and Zhu, H. (2011). Systemic risk contributions. *Federal Reserve Board Finance and Economics Discussion Series*, No. 2011/08.

International Monetary Fund, Bank for International Settlements and Financial Stability Board (2009). *Guidance to assess the systemic importance of financial institutions, markets and instruments: initial considerations (Report to the G-20 Finance Ministers and Central Bank Governors)*. Retrieved from Financial Stability Board website: http://www.financialstabilityboard.org/publications/r_091107c.pdf

International Monetary Fund (2011). *Macroprudential policy: An organizing framework*. Retrieved from International Monetary Fund Monetary and Capital Markets Department website: www.imf.org/external/np/pp/eng/2011/031411.pdf

International Monetary Fund (2012). *Macrofinancial stress testing—Principles and practices.* Retrieved from International Monetary Fund Monetary and Capital Markets Department website: http://www.imf.org/external/np/pp/eng/2012/082212.pdf

İsmihan, M., Dinçergök, B. and Cilasun S.M. (2013). Finance, instability, debt and growth: The Turkish case, 1980-2010. Paper prepared for the EY International Congress on Economics I, Ankara. Retrieved from http://www.ekonomikyaklasim.org/eyc2013/?download=Paper%20271.pdf

İsmihan, M. and Özkan, F.G. (2012).Public debt and financial development: A theoretical exploration. *Economic Letters*, 115, 348-351.

Jacobson, T., Lindé, J. and Roszbach, K. (2005). Exploring interactions between real activity and the financial stance. *Sveriges Riksbank Working Papers*, No. 184.

Kara, H. (2011). Monetary policy under global imbalances: The Turkish experience. Speech at "BIS Chief Economist Meeting", Basel. Retrieved from http://www.tcmb.gov.tr/yeni/iletisimgm/H.Kara_BIS.pdf

Kattai, R. (2010). Credit risk model for the Estonian banking sector. *Bank of Estonia Working Paper Series*, No. 1/2010.

Kearns, A. (2004). Loan losses and the macroeconomy: A framework for stress testing credit institutions' financial well-being. *Central Bank of Ireland Financial Stability Report*, 2004, 111-121.

Küçüközmen, C. and Yüksel, A. (2006). *A macroeconometric model for stress testing credit portfolio*. Paper presented at 13th Annual Conference of the Multinational Finance Society, Edinburgh, UK).

Louzis, D. P., Vouldis, A. T. and Metaxas, V. L. (2010). Macroeconomic and bank-specific determinants of non-performing loans in Greece: A comparative study of mortgage, business and consumer loan portfolios. *Bank of Greece Working Papers*, No. 118.

Lütkepohl, Helmut (2005). *New introduction to multiple time series analysis*. Berlin: Springer.

Marcucci, J. and Quagliariello, M. (2008). Is bank portfolio riskiness procyclical? Evidence from Italy using a vector autoregression. *University of York in Discussion Papers*, No. 05/09.

Neftçi, S. N. (1984). Are economic time series asymmetric over the business cycle? Journal of Political Economy, 92(2), 307-328.

Nickell, S. (1981). Biases in dynamic models with fixed effects. *Econometrica,* 49, 1417-1426.

Nkusu, M. (2011). Nonperforming loans and macrofinancial vulnerabilities in advanced economies. *International Monetary Fund Working Paper*, No. 11/161.

Öcal, N. and Osborne, D. R. (2000). Business cycle nonlinearities in UK consumption and production. *Journal of Applied Econometrics*, 15, 27–43.

Öniş, Z. and Riedel, J. (1993). Economic crises and long-term growth in Turkey. World Bank Economic Studies, No 11744.

Packer, F. and Zhu, H. (2012). Loan loss provisioning practices of Asian banks. *Bank for International Settlements Working Papers*, No 375.

Pain, D. (2003). The provisioning experience of the major UK banks: A small panel investigation. *Bank of England Working Papers*, No. 177.

Pesola, J. (2005). Banking fragility and distress: An econometric study of macroeconomic determinants. *Bank of Finland Research Discussion Papers*, No. 13.

Quagliariello, M. (2006). Bank's riskiness over the business cycle: A panel analysis on Italian intermediaries. *Applied Financial Economics*, 17(2), 119-138.

Rinaldi, L. and Sanchis-Arellano, A. (2006). Household debt sustainability what explains household non-performing loans? An empirical analysis. *European Central Bank Working Paper Series*, No. 570.

Roodman, D. (2006). How to do xtabond2: An introduction to “difference” and “system” GMM in Stata. *Center for Global Development Working Papers*, No. 103.

Salas, V. and Saurina, J. (2002). Credit risk in two institutional regimes: Spanish commercial and savings banks. *Journal of Financial Services Research*, 22(3), 203-224.

Sargan, J. D. (1958). The estimation of economic relationships using instrumental variables. *Econometrica*, 26, 393-415.

Scharnagl, M. and Tödter, K.-H. (2004). How effective are automatic stabilisers? Theory and empirical results for Germany and other OECD countries. *Bundesbank Discussion Paper*, No. 21/2004.

Schmieder, C., Puhr, C. and Hasan, M. (2011). Next generation balance sheet stress testing. *International Monetary Fund Working Paper*, No. 11/83.

Sichel, D. E. (1993) Business Cycle Asymmetry: A Deeper Look. *Economic Inquiry*, 31(2), 224-36.

Sims, C. A. (1980). Macroeconomics and reality. *Econometrica*, 48, 1–48.

Sonbul İskender, E. (2012). Türk bankacılık sistemi kredi riski için bir makroekonomik stres testi modeli uygulaması. *Banking Regulation and Supervision Agency Bankacılık ve Finansal Piyasalar*, 6(1), 9-44.

Sorge, M. and Virolainen, K. (2006). A comparative analysis of macro stress-testing methodologies with application to Finland. *Journal of Financial Stability*, 2, 113–151.

Stolz, S. and Wedow, M. (2005). Banks' regulatory capital buffer and the business cycle: evidence for German savings and cooperative banks. *Bundesbank Discussion Paper*, No. 7/2005.

Teräsvirta, T. and Anderson, H. M. (1992). Characterizing nonlinearities in business cycles using smooth transition autoregressive models. *Journal of Applied Econometrics*, 7, 119.

Tsay, R. S. (1998). Testing and modeling multivariate threshold models. *Journal of American Statistical Association*, 93(443), 1188-1202.

Tsay, R. S. (2010). *Analysis of financial time series*. New Jersey: John Wiley and Sons.

Undersecretariat of Treasury (2001). *Türkiye'nin güçlü ekonomiye geçiş programı*. Retrieved from Central Bank of the Republic of Turkey's website: http://www.tcmb.gov.tr/yeni/duyuru/eko_program/program.pdf

Vazquez, F., Tabak, B. M. and Souto, M. (2010). A macro stress test model of credit risk for the Brazilian banking sector. *Banco Central do Brasil Working Paper Series*, No. 226.

Verbeek, M. (2004). A guide to modern econometrics. Chichester: John Wiley and Sons.

Virolainen, K. (2004). Macro stress testing with a macroeconomic credit risk model for Finland. *Bank of Finland Research Discussion Papers*, No. 18/2004

Worrell, D. (2004). Quantitative assessment of the financial sector: An integrated approach. *International Monetary Fund Working Paper*, No. 04/153.

APPENDICES

APPENDIX A: Comparing the Results of Models Considering Possible Structural Breaks

In order to consider possible structural breaks in the data, we use three dummy variables.

- **Dummy variable 1 (D1):** First dummy variable takes the value 1 for the period **2004:3 -2004:4** and zero otherwise.
- **Dummy variable 2 (D2):** Second dummy variable takes the value 1 for the period **2006:5-2006:6** and zero otherwise.
- **Dummy variable 3 (D3):** Third dummy variable takes the value 1 for the period **2008:11 -2010:3** and zero otherwise.

Hence, in addition to the explanatory variables, i.e. industrial production, CPI, interest rate and banking sector total loans, intercept, which takes 1 for observed structural breaks and 0 otherwise, and slope dummy variables have been included in the regressions. Slope dummy variables are formed by multiplying the intercept dummy (*Dummy*) by each of the explanatory variables (*Dummy* times the name of the explanatory variable indicates the slope dummy variable for that variable, for example *Dummy04*CPI* denotes the slope dummy variable, which is obtained by the intercept dummy for the period 2004:03-2004:04 times the variable CPI).

A1 VAR Models

In the first stage, we include all of these dummy variables (# 1, 2 and 3) in the regressions. And then taking into consideration observed structural breaks, we construct alternative models. Last, by checking the value of AIC, we try to choose the best linear VAR model. Accordingly, we examine all possible model options with different dummy variables (Table A1):

- **Model 1:** It includes all intercept (D1, D2 and D3) and slope dummy variables. We employ 3 intercept and 12 slope dummy variables.
- **Model 2:** It includes D1 and D2 intercept and related slope dummy variables.
- **Model 3:** It includes D1 and D3 intercept and the related slope dummy variables.
- **Model 4:** It includes D2 and D3 intercept and the related slope dummy variables.
- **Model 5:** It includes only D1 intercept and the related slope dummy variables.
- **Model 6:** It includes only D2 intercept and related slope dummy variables.
- **Model 7:** It includes only D3 intercept and related slope dummy variables.
- **Model 8:** It includes slope dummy variables for D1, D2 and D3. Hence, we employ only 12 slope dummy variables.
- **Model 9:** It includes slope dummy variables for D1 and D2.
- **Model 10:** It includes slope dummy variables for D1 and D3.
- **Model 11:** It includes slope dummy variables for D2 and D3.
- **Model 12:** It includes a slope dummy variable only for D1.
- **Model 13:** It includes a slope dummy variable only for D2.
- **Model 14:** It includes a slope dummy variable only for D3.
- **Model 15:** It includes only slope dummy variables for D1 and both intercept and slope dummy variables for D2 and D3.
- **Model 16:** It includes only slope dummy variables for D2 and both intercept and slope dummy variables for D1 and D3.
- **Model 17:** It includes only slope dummy variables for D3 and both intercept and slope dummy variables for D1 and D2.

- **Model 18:** It includes only slope dummy variables for D1 and D2 and both intercept and slope dummy variables for D3.
- **Model 19:** It includes only slope dummy variables for D1 and D3 and both intercept and slope dummy variables for D2.
- **Model 20:** It includes only slope dummy variables for D2 and D3 and both intercept and slope dummy variables for D1.
- **Model 21:** It includes only slope dummy variables for D1 and both intercept and slope dummy variables for D2.
- **Model 22:** It includes only slope dummy variables for D2 and both intercept and slope dummy variables for D1.
- **Model 23:** It includes only slope dummy variables for D1 and both intercept and slope dummy variables for D3.
- **Model 24:** It includes only slope dummy variables for D3 and both intercept and slope dummy variables for D1.
- **Model 25:** It includes only slope dummy variables for D2 and both intercept and slope dummy variables for D3.
- **Model 26:** It includes only slope dummy variables for D3 and both intercept and slope dummy variables for D2.
- **Model 27:** The model includes no dummy variable.

Table A1: AIC values for the models

Model	AIC
Model 1	620
Model 2	652
Model 3	595
Model 4	599
Model 5	626
Model 6	630
Model 7	574 ✓

Model 8	606
Model 9	636
Model 10	589
Model 11	592
Model 12	618
Model 13	623
Model 14	574
Model 15	613
Model 16	613
Model 17	622
Model 18	605
Model 19	614
Model 20	614
Model 21	644
Model 22	644
Model 23	587
Model 24	597
Model 25	592
Model 26	614
Model 27	603

We find that the Model 7 has the lowest AIC value, which includes only third dummy variable (intercept and slope dummies) that takes the value 1 for the period 2008:11 -2010:3 and zero otherwise.

Table A2: Nonlinearity test results

Lag	m0[1]	Variables[2]							
		Industrial production		CPI		Interest Rate		Loans	
		C(d)[3]	p-value	C(d)[3]	p-value	C(d)[3]	p-value	C(d)[3]	p-value
1	40	23.07	*0.98524*	29.09	*0.8991*	70.47	***0.00207***	23.34	*0.98354*
1	50	21.39	*0.99299*	26.64	*0.94804*	57.98	*0.03276*	17.05	*0.99944*
2	40	20.33	*0.99588*	25.26	*0.96658*	38.45	*0.54031*	22.84	*0.98661*
2	50	19.7	*0.99707*	24.23	*0.97678*	52.32	*0.09185*	27.79	*0.92775*
3	40	19.46	*0.99743*	32.62	*0.78981*	48.08	*0.17822*	28.07	*0.92204*
3	50	19.78	*0.99693*	30.85	*0.85017*	45.13	*0.26611*	24.3	*0.97621*
4	40	20.63	*0.9952*	27.48	*0.93365*	42.99	*0.34438*	32.08	*0.80957*
4	50	20.92	*0.99443*	26.42	*0.95134*	45.09	*0.26733*	24.73	*0.97217*
5	40	23.92	*0.97933*	27.81	*0.92741*	38.05	*0.55829*	29.24	*0.89527*
5	50	19.63	*0.99718*	25.52	*0.96345*	42.67	*0.35698*	21.44	*0.99285*
6	40	15.72	*0.9998*	24.48	*0.97453*	41.45	*0.40723*	28.41	*0.91474*
6	50	17.26	*0.99936*	19.79	*0.99692*	46.42	*0.22474*	22.69	*0.98744*
7	40	7.62	*1*	24.05	*0.97829*	40.44	*0.45094*	32.35	*0.79969*
7	50	7.55	*1*	23.46	*0.98271*	41.21	*0.41762*	27.96	*0.92428*
8	40	7.61	*1*	22.13	*0.99015*	41	*0.42649*	32.65	*0.78903*
8	50	7.06	*1*	25.86	*0.95923*	40.68	*0.44016*	35.28	*0.68263*
9	40	20.59	*0.9953*	49.04	*0.15476*	44.24	*0.29724*	39.54	*0.49062*
9	50	19.36	*0.99758*	60.09	*0.02148*	46.38	*0.22592*	35.07	*0.69144*
10	40	38.87	*0.52103*	88.43	***0.00002***	50.83	*0.11721*	47.8	*0.18538*
10	50	26.14	*0.9554*	63.36	*0.01075*	43.86	*0.31132*	38.52	*0.53712*
11	40	28.1	*0.92149*	60.52	*0.01967*	59.52	*0.02411*	41.62	*0.40014*
11	50	27.32	*0.9365*	60.16	*0.02116*	60.83	*0.01842*	38.2	*0.55171*
12	40	29.53	*0.88793*	68.89	*0.00303*	67.86	*0.00387*	50.56	*0.12237*
12	50	29.15	*0.8976*	64.18	*0.00897*	58.78	*0.02798*	49.2	*0.151*

Notes:

1) m0 indicates the starting point of the recursive least squares estimation *and equals to 3 or 5 times the square root of n, number of observations.

2) Industrial production index, consumer price index and banking sector total loans are logged differenced indicating 12-month change.

3) C(d) test statistic check whether the predictive residuals, obtained from recursive least squares estimation, are white noise under the null hypothesis of linearity.

After taking the possible structural breaks into account, i.e. considering the Model 7 as the baseline model, we check whether any nonlinearity still exists in the data. For the nonlinearity test, we follow Tsay's 1998 approach. The order of the VAR model is 1. We test all the variables in the model. The p values of significant test statistics are shaded in Table A2. The best transition variable is inflation and the delay parameter is 10. The second best transition variable is interbank overnight deposit rates and the related delay parameter is 1. Interest rates is one of the major policy tools, which is effectively used after the introduction of inflation targeting regime, and it is effective in determining the cycles both in financial sector and real sector. Hence, later on, as we will do in nonlinearity VAR modelling, we prefer to choose the overnight interest rate as the transition variable.

In sum, after taking the possible structural breaks into the account, there still remains some nonlinearity in the data.

For a nonlinear VAR model setup, we again try to control for the structural break for the period from November 2008 to March 2010 due to the global crisis and the extraordinary measures taken against it both abroad in Turkey in the data. We construct four nonlinear VAR models:

a. **Model 1:** Nonlinear VAR model with both intercept and slope (interaction terms) dummy variables.
b. **Model 2:** Nonlinear VAR model with only intercept dummy variable.
c. **Model 3:** Nonlinear VAR model with only slope dummy variables.
d. **Model 4:** Nonlinear VAR model without controlling for the break in 2008:11-2010:03.

Considering the nonlinearity test results in the previous section, we use interbank overnight deposit rates as the transition variable with delay parameter being equal to 1.

Table A3: AIC values for the models

Model	AIC
Model 1	574✓
Model 2	613
Model 3	579
Model 4	603

As it is given in Table A3, the calculated AIC values indicate that the best nonlinear VAR model is Model 1 which includes both the intercept and slope dummy variables for the period 2008:11-2010:03.

A2 Panel Data Models

A2.1 Static Panel Data Models

For the panel data model, we try to control for the break in the data due to global crisis. We construct four setups for each fixed and random effects panel data models:

a. **Model 1:** Static panel data model with both intercept and slope (interaction terms) dummy variables.
b. **Model 2:** Static panel data model with only intercept dummy variable.
c. **Model 3:** Static panel data model with only slope dummy variables.
d. **Model 4:** Static panel data model without controlling for the break in 2008:11-2010:03.

Table A4: AIC values for the static panel data models

Model	AIC	
	Fixed effects	Random effects
Model 1	7161✓	7176✓
Model 2	7218	7223
Model 3	7167	7178
Model 4	7260	7238

As it is given in Table A4, the calculated AIC values indicate that the best fixed effects and random effects panel data model is Model 1, which includes both the intercept and slope dummy variables for the period 2008:11-2010:03.

A2.2 Dynamic Panel Data Model

For the dynamic panel data model, we try to control for the break in the data due to global crisis. We construct four setups for each fixed and random affects panel data models:

a. **Model 1:** Dynamic panel data model <u>with both intercept and slope</u> (interaction terms) dummy variables.
b. **Model 2:** Dynamic panel data model <u>with only intercept</u> dummy variable.
c. **Model 3:** Dynamic panel data model <u>with only slope</u> dummy variables.
d. **Model 4:** Dynamic panel data model <u>without</u> controlling for the break in 2008:11-2010:03.

Table A5: AIC values for the dynamic panel data model

Model	AIC
Model 1	3632.61
Model 2	3628.79✓
Model 3	3632.61
Model 4	3634.39

As it is given in Table A5, the calculated AIC values indicate that the best dynamic panel data model is Model 2, which includes only the intercept dummy variable for the period 2008:11-2010:03.

A2.3 Nonlinear Panel Data Model

For a nonlinear panel data model setup, we try to control for the break in the data due to global crisis. We construct four nonlinear panel data models:

a. **Model 1:** Nonlinear panel data model with both intercept and slope (interaction terms) dummy variables.
b. **Model 2:** Nonlinear panel data model with only intercept dummy variable.
c. **Model 3:** Nonlinear panel data model with only slope dummy variables.
d. **Model 4:** Nonlinear panel data model without controlling for the break in 2008:11-2010:03.

Table A6: AIC values for the nonlinear panel data model

Model	AIC
Model 1	7161✓
Model 2	7218
Model 3	7166
Model 4	7260

As it is given in Table A6, the calculated AIC values indicate that the best nonlinear panel data model is Model 1, which includes both the intercept and slope dummy variables for the period 2008:11-2010:03.

APPENDIX B: Comparing the Forecast Performance of Linear and Nonlinear VAR Models

We employ both linear and nonlinear VAR models to forecast the future values of macroeconomic and macrofinancial variables, namely industrial production, consumer price index, interbank overnight deposit rate and banking sector total loans. Then, we use these forecasted values, which are obtained from linear and nonlinear VAR models, in the panel data models to predict future values of the nonperforming loans of banks, which is a proxy variable for the credit risk of banks. By comparing the predicted values and the actual values of the nonperforming loans, we can evaluate which panel data model delivers superior prediction performance for credit risk by employing several measures such as root mean square error, mean absolute percentage error and vice versa. Such approach also allows us to conclude which VAR model produces more precise forecasted values and hence whether linear or nonlinear VAR model structure should be adopted. Hence, we make a decision between linear and nonlinear VAR models based on an evaluation about their performance in producing good forecast values. Our main aim is not to choose the best VAR model, but find the best performing VAR model in forecasting the macroeconomic and macrofinancial variables since we primarily interested in obtaining forecasted values for macro indicators.

As it is evident from the Table B1 and Table B2, the empirical results show that nonlinear VAR and nonlinear panel data models provide better results.

Table B1: <u>Linear VAR Model:</u> Forecasting Results for Log(NPL Ratio)
(Estimation period: 2002:12-2011:12)

	Linear Fixed Effects	**Random Effects**	**Dynamic Panel**	**Nonlinear Fixed Effects**	**Actual Values**
2012:01	0.2729	-1.0094	-1.8609	-1.2946	-1.5578
2012:02	0.2858	-0.9977	-1.6827	-1.2898	-1.5557
2012:03	0.2982	-0.9866	-1.5294	-1.2894	-1.5611
2012:04	0.3067	-0.9800	-1.3965	-1.2897	-1.5633
2012:05	0.3146	-0.9743	-1.2820	-1.2918	-1.5681
2012:06	0.3265	-0.9651	-1.1829	-1.2909	-1.5755
2012:07	0.3341	-0.9603	-1.0973	-1.2923	-1.5655
2012:08	0.3385	-0.9587	-1.0237	-1.2960	-1.5533
2012:09	0.3449	-0.9553	-0.9602	-1.2988	-1.5305
2012:10	0.3517	-0.9515	-0.9055	-1.3016	-1.5283
2012:11	0.3581	-0.9480	-0.8584	-1.3044	-1.5264
2012:12	0.3594	-0.9494	-0.8176	-1.3087	-1.5435
RMSE	3.5227	0.3398	0.2132	0.0663	
MAPE	120.951	37.5339	26.3585	16.5243	
Correlation	0.5918	0.5206	0.5537	0.7854	1.0000

Table B2: <u>Nonlinear VAR Model:</u> Forecasting Results for Log(NPL Ratio)
(Estimation period: 2002:12-2011:12)

	Linear Fixed Effects	**Random Effects**	**Dynamic Panel**	**Nonlinear Fixed Effects**	**Actual Values**
2012:01	0.2763	-1.0101	-1.8623	-1.2821	-1.5578
2012:02	0.2791	-1.0009	-1.6815	-1.3032	-1.5557
2012:03	0.2919	-0.9854	-1.5267	-1.3135	-1.5611
2012:04	0.3136	-0.9728	-1.3964	-1.2869	-1.5633
2012:05	0.3164	-0.9669	-1.2800	-1.3069	-1.5681
2012:06	0.3384	-0.9540	-1.1832	-1.2830	-1.5755
2012:07	0.3469	-0.9517	-1.0990	-1.2749	-1.5655
2012:08	0.3400	-0.9539	-1.0226	-1.3057	-1.5533
2012:09	0.3459	-0.9470	-0.9577	-1.3196	-1.5305
2012:10	0.3572	-0.9367	-0.9024	-1.3252	-1.5283
2012:11	0.3702	-0.9259	-0.8551	-1.3265	-1.5264
2012:12	0.3786	-0.9202	-0.8143	-1.3274	-1.5435
RMSE	3.5425	0.3509	0.2147	**0.0624**	
MAPE	121.2415	38.1342	26.4460	**15.9468**	
Correlation	0.5225	0.5317	0.5558	**0.7855**	1.0000

APPENDIX C: Turkish Summary

Kredi riskine yönelik bir makro stres testi gerçekleştirmek üzere tezde, bağımsız ancak birbirini tamamlayıcı bir model dizisinin kullanımı önerilmektedir. Önce, finansal istikrarın makroekonomik istikrarla bağlantısı kurularak makroekonomik değişkenlerle makrofinansal değişkenler arasındaki ilişki analiz edilmektedir. Ardından, tahsili gecikmiş alacaklar, durağan ve devingen panel veri teknikleri aracılığıyla, VAR modeldeki makroekonomik ve makrofinansal değişkenler ile bankalara özgü göstergeler kullanılarak tahmin edilmektedir.

2008 küresel krizinde, bir ülkedeki sektörler ve kuruluşlar arasında olduğu kadar, ülkeler arasında da sirayet etkisinin görülmesi ve dolayısıyla sistemik riskin öne çıkması, makro ihtiyati politikaların önemini ortaya koymuştur. Küresel krizin ardından yalnızca mevcut düzenleme çerçevesinin kapsamının genişletilerek daha sağlam bir sistem oluşturulamayacağı görülmüştür. Sermaye ve likidite yeterliliği düzenlemeleri gibi mikro ihtiyati araçlar, aşırı risk üstlenen finansal pozisyonları tespit etmede ve finansal sistemde kırılganlıkların artmasını önlemede yetersiz kalmıştır. Hatta bazı düzenleyici finansal tedbirler, uygulamada finansal sistemdeki döngüselliği daha da artırarak finansal sistemdeki kırılganlıkları beslemiştir. Bu nedenle, dışsal şoklar gibi tetikleyici olaylar, genellikle bu türden finansal koşulların varlığı halinde finansal sistemdeki kırılganlıkları bir krize dönüştürebilmektedir.

Sistemik risklerin ele alınması gereken iki boyutu bulunmaktadır: Risklerin birikmesi ve dışsal şoklar, dolayısıyla sirayet etkisi. Borio (2011) söz konusu unsurları makro ihtiyati politikaların boyutları olarak ele almakta ve iki grupta sınıflandırmaktadır: Zaman boyutu ve kesit boyutu. Zaman boyutu, finansal sistemin doğası gereği söz konusu olan döngüselliği ifade etmektedir. Kesit boyutu ise finansal sistemin parçası olan piyasalar ve kuruluşlar gibi temel unsurlar arasındaki etkileşime ve bu etkileşimin ortaya çıkardığı riskin büyüklüğüne karşılık gelmektedir. Bu bağlamda, finansal gerilimlere kaynaklık edebilecek her bir boyuta yönelik bir politika çerçevesi oluşturmak mümkündür.

Bankaların bilançoları zaman içerisinde iktisadi çevrimlere paralel olarak hareket etmekte ve dolayısıyla döngüsellik gündeme gelmektedir. Diğer taraftan, bankaların bilançolarında kredi riski başta olmak üzere taşıdıkları risklerin gerçekleşmesi döngüsellik karşıtı bir nitelik göstermektedir. Finansal sistemdeki gelişmelerin, iktisadi çevrimlerin daha sertleşmesine yol açması ve reel sektördeki gelişmelerin ise finansal istikrarsızlığa neden olabilmesi nedeniyle, döngüsellik, bu anlamda, birbirini besleyen mekanizmaların varlığına işaret etmek amacıyla kullanılmaktadır.

Kamu maliyesinde vergi ile kamu harcamalarındaki döngüsel nitelikteki değişiklikler, milli hasıla üzerinde istikrar sağlayıcı etkiler yaratması nedeniyle, otomatik dengeleyici olarak adlandırılmaktadır (Scharnagl and Tödter, 2004). Benzer bir biçimde, finansal sistemde de, stres dönemlerinde reel ekonomi ile finansal sistem arasındaki olumsuz etkileşimleri dizginleyecek ve çevrimlerin aksi istikametinde hareket edecek otomatik dengeleyicilere ihtiyaç bulunmaktadır. Bu nedenle, krizin hemen ardından, finansal istikrarın korunmasında sağlayabileceği katkılar nedeniyle, konu, makro ihtiyati politika çerçevesinde önemli bir yer edinmiş ve politika yapıcılar açısından giderek daha önemli hale gelmiştir.

Politika yapıcılar için temel problem, iktisadi görünümün olumlu seyrettiği dönemlerde, finansal sistemde yeterli miktarda, sistemi dalgalanmalara karşı koruyacak, gerçekleştirilmesi kolay ve ucuzken, finansal tamponların oluşturulmamasıdır. Dolayısıyla, finansal sistemin kriz veya bozulan iktisadi görünüm nedeniyle oluşan zararlarını karşılaması, reel ekonomideki koşulları daha da kötüleştirmeden gerçekleştirilememektedir. Bunun bir sonucu olarak, finansal sistem bünyesinde çalışan mekanizmalar şokların etkilerini azaltmak yerine artırıcı bir rol oynamaktadır. Bu nedenle, varlık fiyatlarında aşırı şişme oluşmaması ve fiyat düşüşlerinin kontrollü olması için finansal sisteme yönelik döngüsellik karşıtı bir düzenleme çerçevesine ihtiyaç duyulmuştur. Bu gereksinime paralel olarak, BIS (2008) bankaların beklenen ve beklenmeyen zararları karşılama kapasitelerini geliştirmek üzere dinamik karşılık ayırma ve sermaye tamponları gibi bir takım uluslararası finansal araçlar ve kurallar hazırlamıştır. Sermaye tamponu genellikle bir bankanın mevcut sermaye oranı ile yasal asgari sermaye oranı arasındaki fark olarak tanımlanmaktadır.

Basel Komitesi (BIS BCBS, 2011) döngüsellik konusunda bir çerçeve oluşturmuş ve bankacılık sektörünün dayanıklılığının arıtılması için şu dört hedefi belirlemiştir:

- Finansal gerilim dönemlerinde kullanmak üzere bankaların özkaynaklarını kullanarak sermaye tamponları oluşturması,
- Bankacılık sektörünün aşırı kredi genişlemesinin yaşandığı dönemlerde oluşan risklerden korunması,
- İleriye yönelik karşılık ayırma uygulamasının güçlendirilmesi,
- Asgari sermaye yeterlilik oranı düzenlemelerinin neden olduğu döngüsellik dikkate alınarak gerekli düzeltmelerin yapılması.

Finansal piyasalar ve politika yapıcılığında yaşanan son gelişmelere paralel olarak, finansal sistemdeki risklerin izlenmesi ve ölçülmesi için oluşturulan modellere yönelik yeni yaklaşımların ortaya çıktığı görülmektedir. Gerek ulusal gerekse uluslararası alanda, mevcut düzenleyici çerçevelerin iyileştirilmesi için çalışmalar sürmektedir. Bu amaca yönelik olarak, küresel krizin ortaya çıkmasının ardından G20 bünyesinde bir dizi çalışma yürütülmüş ve G20, Finansal İstikrar Kurulu (Financial Stability Board – FSB) ile Uluslararası Ödemeler Bankası (Bank for International Settlement – BIS) Basel Bankacılık Gözetim ve Denetim Komitesi'nden (Basel Committee on Banking Supervision – BCBS) yeni bir uluslararası bankacılık standartları seti hazırlamasını istemiştir. Bu çerçevede, G20 üyesi ülkelerin gözetim ve denetim otoritelerinden uzmanlar ve politika yapıcılar bir araya gelerek, mevcut Basel II düzenlemelerini tamamlayıcı nitelikte bir yeni kural seti oluşturmuştur. Finansal sistemin sağlamlığı ile doğrudan bağlantılı bu yeni kural setinde, sermayenin niteliğinin ve niceliğinin iyileştirilmesi (daha güncel bir sermaye tanımı ile daha yüksek asgari sermaye oranları), sermaye tamponlarının oluşturulması (zaman içerisinde döngüsel hareketlerin tersine hareket etmesi beklenen ilave sermaye oranları), aşırı borçlanmayı engellemek üzere bir kaldıraç oranının belirlenmesi konuları yer almaktadır.

Uluslararası finansal kuralları yeniden düzenleme çalışmaları dışında, ülkeler itibarıyla da finansal sistemi düzenlemeye yönelik bir dizi çalışma bulunmaktadır. Buna göre, Amerika Birleşik Devletleri, krizin hemen ardından yasalaşan Dodd-Frank düzenlemesi ile bu çerçevede ilk yasal tedbire başvuran ülkedir. Finansal tehditlerin izlenmesi ve gerekli düzenlemelerin yapılması ile krizlerin etkin bir biçimde çözümlenmesi konusunda Avrupa Birliği'nde de çalışmalar yürütülmektedir. Bu amaca yönelik olarak hazırlanan Larosiere Raporu (2009) Avrupa Merkez Bankası'nın makro ihtiyati bir yaklaşım benimsemesini ve şu üç alana önem vermesini salık vermektedir:

Finansal istikrar. Artık yaygın bir biçimde finansal istikrarın korunması için makro ihtiyati politikaların oluşturulması ve döngüsellik karşıtı araçların kullanılması gerektiği düşünülmektedir.

Erken uyarı sistemi. Finansal kırılganlıklar nedeniyle oluşan risklerin izlenebilmesi amacıyla erken uyarı sistemlerinin etkinliğinin artırılması gerektiği vurgulanmaktadır. Erken uyarı sistemleri ile politika yapıcıların tüm bankacılık sisteminin finansal gerilime girme olasılığı konusunda bilgilendirilmesi ve dolayısıyla politika yapıcıların olası bir krize karşı gerekli tedbirleri zamanında alabilmelerine olanak tanınması amaçlanmaktadır.

Makro stres testi. Dışsal şokların bankacılık sisteminin bütünü üzerindeki etkilerinin ölçülebilmesi için makro stres testlerine ihtiyaç bulunmaktadır.

Özet olarak, etkin bir kriz önleme çerçevesinin uygulamaya konulabilmesi için, politika yapıcılar şu mekanizmaların etkin bir işlerliğe sahip olduğundan emin olmalıdır: Finansal sistemin bütününü dikkate alan makro ihtiyati politikalar ve araçlar, kırılganlıkların tespit edilebilmesi ve bankacılık sektöründeki stresin derecesinin ölçülebilmesi için etkin bir erken uyarı sistemi ve bankacılık sektörünün dışsal şoklara olan duyarlılığının ölçülebilmesi için makro stres testleri.

Yaşanan son küresel kriz, sistemin bütününü dikkate alan makro ihtiyati politikaların önemini ortaya koymuş ve finansal sisteme yönelik tehditlere karşı etkin sonuçlar alınabilmesi için gerekli araçları ön plana çıkarmıştır. IMF, BIS ve FSB (2009) sistemik riski, finansal hizmetlerin kesintiye uğraması olarak tanımlamaktadır. Buna göre, finansal hizmetlerin kesintiye uğraması, finansal sistemin bir bölümünde ya da bütününde yaşanan sorunlardan ileri gelebilmekte ve reel ekonomi üzerinde bir takım olumsuz sonuçlar yaratabilmektedir. IMF (2011) makro ihtiyati politikaları sistemin bütününe yönelik, diğer bir deyişle sistemik, finansal riskleri sınırlandırmaya veya gidermeye yönelik politikalar olarak tanımlamaktadır. Bu bağlamda, IMF (2011), makro ihtiyati politikaların temel amacının sistemik risklerin oluşmasını önlemek olduğunu öne sürmektedir. Küresel krizden çıkarılacak söz konusu dersleri ve dolayısıyla finansal tehditlere karşı mevcut finansal sistemi izleme mekanizmalarındaki revizyon ihtiyacını dikkate alarak, ulusal otoriteler ve uluslararası kuruluşlar finansal sistemin bütününü gözeten politikalara daha fazla vurgu yapmaya ve esas olarak erken uyarı sistemi, döngüsellik ve makro stres testi gibi alanlara yoğunlaşmaya başlamıştır.

Bu bağlamda, bazı merkez bankaları (örneğin İngiltere, Norveç ve Avusturya) halihazırda söz konusu alanlarda çalışmaya başlamıştır. Söz konusu merkez bankaları, erken uyarı sistemi, döngüsellik ve makro stres testi araçlarını belirli ölçülerde bir araya getirecek mekanizmalar üretmeye çalışmaktadır. Örnek vermek gerekirse, bu türden bir yaklaşımla (genellikle VAR yaklaşımına dayalı)bir makro stres testi modeli, bankaların veya firmaların iflas olasılıklarını tahmin etmek üzere kurgulanan bir model ile ilişkilendirilerek, modeller birlikte, etkileşim içinde kullanılabilmektedir. Bu tip bir yaklaşım, aynı zamanda, finansal sistem ile reel ekonomi arasındaki etkileşimleri de daha sağlıklı bir şekilde analiz etme imkanı sunmaktadır. Bu açıdan, bir VAR modeli, diğer makroekonomik modellerde olduğu gibi teorik kurguya ilişkin hususların getirdiği sorunlara çok fazla maruz kalmadan, etkili ve güvenilir tahminler üretebilmekte ve finansal sistemin bir stres testine tabi tutulabilmesi için gerekli makroekonomik senaryoların oluşturulmasına olanak tanımaktadır. Buna ilaveten, VAR modellerin sağladığı diğer bir fayda, makroekonomik modele finansal sistemin bütününü temsil eden bir denklem eklenerek, stres koşulları altında banka bilançolarının reel ekonomi üzerinde yaratacağı ikincil etkileri ölçmenin mümkün hale gelmesidir.

Uygulamada, akademik ve profesyonel kuruluşlar tarafından hazırlanan çalışmalarda bankacılık sektörünün genel risklilik düzeyi içerisindeki payı dikkate alınarak sıklıkla kredi riskinin ölçülmesi hedeflenmektedir. Gelişmiş ülkelerde kredi riski, bankacılık sektörünün toplam riskinin ortalama yüzde 70 ilâ 80'inini oluşturmaktadır. Kredi riski uygulamada banka bazında veya ipotekli konut kredileri ya da firma kredileri gibi kredi türleri itibarıyla sektörel bazda panel veri teknikleri kullanılarak tahmin edilmektedir. Bankacılık sektörü kredilerinin ekonominin genel hareketleri doğrultusunda döngüsel bir özellik göstermesi nedeniyle, tüm diğer unsurlar sabitken, iktisadi dalgalanma üzerinde belirleyici olan temel göstergeler bankaların kredi riskini açıklamada hatırı sayılır bir ağırlığa sahiptir. Bankacılık sektörünün genel riskliliğinin belirli bir bölümü üzerinde yoğunlaşmak yerine, alternatif bir yaklaşım olarak, makroekonomik ve bankalara özgü göstergeler kullanılarak bankaların temerrüt olasılıklarının tahmin edilmesi yöntemi de düşünülebilir. Bu tip bir yöntem, doğası gereği erken uyarı göstergelerinin belirlenmesine de yardımcı olacağı için etkinliği yüksek olabilecektir. Bu durum, özellikle finansal istikrarın bozulması ihtimaline karşı tedbirlerin zamanında alınabilmesi ve söz konusu kararların sağlam değerlendirmelere dayandırılabilmesi açısından son derece önemlidir. Finansal sistemdeki gelişmelerin doğru bir şekilde izlenebilmesi ve değerlendirilebilmesi ise iyi tanımlanmış ve kurgulanmış bir nicel analiz çerçevesini gerektirmektedir.

Worrell (2004), bu bağlamda, politika yapıcılarına ellerinde mevcut nicel değerlendirme araç ve tekniklerini birbirlerini tamamlayıcı bir biçimde kullanmalarını salık vermektedir. Söz konusu araç ve teknikler ise genellikle finansal gerilimin derecesinin ölçülebilmesi için bir erken uyarı sistemini, stres testi kapsamında kullanılabilecek duyarlılık analizi ve şok senaryoları ile finansal göstergelere ilişkin öngörüleri kapsamaktadır. Sorge ve Virolainen (2006) de bu türden bir bütüncül yaklaşımın önemine vurgu yapmaktadır. Ayrıca, aynı zamanda, stres testleri ile erken uyarı sistemleri arasına bir çizgi çekerek iki aracı birbirinden ayrı tutmaktadır. Erken uyarı sistemleri, kriz olasılıkları üzerine yoğunlaşırken, makro stres testleri ise bir kriz esnasında finansal sistemin göstereceği duyarlılığı ölçmeyi amaçlamaktadır. Bu açıdan, bankaların, muhtemelen bir dışsal şok sonucu oluşan kriz koşulları altında faaliyetlerini ne kadar süre idame ettirebileceklerini bilmek, sağlıklı stratejilerin oluşturulması ve sağlam tedbirlerin alınabilmesi bakımından oldukça önemlidir. Bu nedenle, sermaye tamponlarının (ya da zarar karşılıklarının) konjonktürel dalgalanmalara veya kriz koşullarına olan duyarlılığının analizi ve tahmini hususunu da yukarıda bahsi geçen bütüncül izleme ve değerlendirme çerçevesinin bir parçası olarak görmekte yarar bulunmaktadır.

Makro stres testleri politika yapıcılara, sıradışı ancak gerçekleşmesi olası bir takım senaryolar çerçevesinde finansal sistemin maruz kalacağı zararlara ilişkin bilgi sunmaktadır. Finansal sistemin bir stres testine tabi tutulması genellikle birbirine alternatif iki yolla gerçekleştirilmektedir: Aşağıdan yukarı yaklaşım ve yukarıdan aşağı yaklaşım. Aşağıdan yukarı stres testi yaklaşımında stres testi uygulaması çoğunlukla, reel ekonomiden kaynaklanan bir dışsal şokun bir finansal kuruluşun bilançosu üzerindeki etkisinin ölçülmesi amacını gütmektedir. Finansal kuruluşlar ile düzenleme ve gözetim otoriteleri, en azından geçmişte, esas olarak dışsal şokların tekil kuruluşlar üzerindeki etkileri ile ilgilendiklerinden bu türden bir yönteme daha fazla ilgi göstermektedir. Söz konusu yaklaşım kendi kurgusu içerisinde herhangi bir zafiyet göstermemekle birlikte, sistemin bütününe yansıyacak zararlarla ilgilenildiğinde, aşağıdan yukarı yaklaşım ile elde edilen sonuçların toplulaştırılması ile bulunacak zarar miktarı, finansal sistemin maruz kaldığı zarar miktarını veya diğer bir deyişle toplam risk tutarını doğru bir biçimde yansıtmayacaktır. Söz konusu yaklaşımla elde edilen hesaplamalarda bu türden bir sapma görülmesinin temel nedeni, piyasalar ve kuruluşlar arasındaki etkileşimler ile farklı varlık grupları arasındaki ilişkilerin, diğer bir deyişle, bir bütün olarak sistemik riskin göz ardı edilmesidir. Özellikle son küresel krizin ardından, makro ihtiyati analizlere artan ilgi ile birlikte, yukarıdan aşağı (makro) stres testi çalışmaları yoğunlaşmış ve bu alanda önemli ilerlemeler kaydedilmiştir.

Schmieder vd. (2011) söz konusu yeni uygulamaları "sonraki nesil stres testi uygulaması" olarak tanımlamakta ve bu yeni stres testi çerçevesinin şu dört temel özelliğinden bahsetmektedir:

(1) Senaryoların kurgulanmasında birbiri ile bağlantılı varsayımların yapılabilmesi,

(2) Temel risk faktörlerindeki değişimlerin bankaların ödeme güçleri üzerindeki etkisinin hesaplanabilmesi,

(3) Excel benzeri kullanımı kolay teknik araçlardan yararlanılabilmesi,

(4) Geniş panel veri setlerinin kullanılmasına olanak veren bir çerçeve sunması.

Foglia (2008), makroekonomik ve finansal değişkenlere verilen çoklu şokların finansal sektör üzerindeki etkilerini hesaplamak üzere kullanılacak makro stres testlerine ilişkin üç yaklaşımdan bahsetmektedir:

(1) Yapısal bir ekonometrik model (öngörü amacıyla genellikle merkez bankaları tarafından kullanılan modeller),

(2) VAR modelleri,

(3) İstatistiki modeller.

IMF (2012), IMF'nin 1999 yılından itibaren üye ülkelerin finansal sistemlerini analiz etmek üzere gerçekleştirdiği Finansal Sektör Değerlendirme Programlarından elde edilen bilgi birikimi ve tecrübeler ışığında stres testi uygulamalarına ilişkin yedi ilke önermektedir. Bu çerçevede, stres testi, farklı varsayımsal olay ve senaryolar kapsamında bir portföyün, bir kuruluşun veya bir bütün olarak finansal sistemin kırılganlığını ölçmeye yönelik bir teknik olarak tanımlamaktadır. Söz konusu ilkeler şunlardır:

- Stres testinin kapsamı tam olarak tanımlanmalıdır. Söz konusu ilke, tüm finansal sistemin stres testi kapsamına dahil edilemediği hallerde, teste, sistemik önemi bulunan kuruluşların dahil edilmesini gerektirmektedir.
- Tüm risk yayılma kanalları belirlenmelidir. Söz konusu durum, temel risk yayılma mekanizmalarının saptanmasını ve ilgili kanalların anlaşılmasını gerektirmektedir.
- Bir finansal kuruluşun faaliyetlerinden doğan tüm riskler göz önünde bulundurulmalıdır. Bu ise finansal kuruluşun iş modelinin anlaşılmasını, faaliyet gösterdiği piyasa ile sektörel ve uluslararası risklerinin bilinmesini zorunlu kılmaktadır.
- Yatırımcıların yaklaşımlarının ve bakış açılarının dikkate alınmasında yarar bulunmaktadır.
- Gerçekleşmesi muhtemel olan, ancak gerçekleşmesi düşük ihtimal taşıyan risklere yoğunlaşılmalıdır. Bu ise stres testlerinde, sıradışı ancak gerçekleşmesi olası şokların kullanılmasını gerektirmektedir.
- Stres testi sonuçlarını kamuya açıklarken hassasiyet gösteren hususların vurgulanmasında yarar bulunmaktadır. Dolayısıyla, stres testine ilişkin bir iletişim politikasının varlığı önemlidir.
- “Siyah kuğu” ihtimalinin göz önüne alınmasında yarar bulunmaktadır. Bu ise gerçekleşmesi muhtemel olan ancak düşük ihtimal taşıyan olayların belirlenmesini ve risk aktarım mekanizmalarının tanımlanmasını gerektirmektedir.

IMF (2012) temel amaçları ile uyumlu olarak dört tür stres testi yöntemi tanımlamaktadır. Söz konusu yöntemler şunlardır:

(1) Bir içsel risk yönetim aracı: Yatırımlarının beraberinde getirdiği riskleri değerlendirebilmek amacıyla, finansal kuruluşlar, içsel risk yönetim süreçlerinin bir parçası olarak stres testi kullanmaktadır.

(2) Mikro ihtiyati (gözetim amaçlı) stres testi uygulaması. Basel II risk çerçevesinin birinci yapısal bloğu (asgari sermaye yeterlilik oranı düzenlemeleri) bankaların piyasa riski ve kredi risklerini ölçmek üzere stres testi uygulamalarını öngörmektedir. Aynı zamanda, Basel II risk çerçevesinin ikinci yapısal bloğu (gözetim ve denetim otoritesinin gerçekleştirdiği değerlendirmeler), gözetim ve denetim otoritelerinin bankaları ilâve testler uygulamaya yöneltmesine imkân tanımaktadır.

(3) Makro ihtiyati (izleme amaçlı) stres testi uygulaması. Makro ihtiyati stres testi uygulamaları, finansal sistemin bütününü dikkate almakta ve sistemik riske yol açan unsurlar ile finansal sistemdeki kırılganlıkları belirlemeyi amaçlamaktadır.

(4) Kriz yönetimi esnasında kullanılan stres testi uygulaması. Stres testi uygulamaları, finansal kuruluşların sermaye düzeylerinin yeterli olup olmadığını, ilâve sermaye gereksinimlerinin bulunup bulunmadığını saptamak amacıyla da kullanılabilmektedir. Söz konusu türden stres testi uygulamaları, son küresel krizin ardından oldukça yaygın bir biçimde kullanılmaya başlanmıştır.

Greenlaw vd. (2012) stres testi uygulamalarına ilişkin makro ihtiyati yaklaşım doğrultusunda ilkeler önermektedir. Bu çerçevede, stres testleri, bankacılık sisteminin bir bütün olarak reel ekonomiyi desteleyecek yeterli kapasiteye sahip olup olmadığını değerlendirmek için kullanılacak araçlar olarak görülmektedir. Önerilen ilkeler şunladır:

- Hızlı mevduat çekilişini önlemek için bankalar yeterli miktarda sermaye bulundurmalıdır.
- Finansal sistemin bütününde istikrar korunamadığında, yeterli sermaye oranlarına sahip bankalar da dahil olmak üzere bankacılık sisteminin tümü temerrüt riski ile karşı karşıya kalabilmektedir. Bu nedenle, denetim ve gözetim otoritesi, bir bütün olarak finansal sistemin istikrarına öncelik vermelidir.
- Sermaye gereksinimlerinin oransal olduğu kadar tutar olarak da değerlendirilmesi önemlidir. Bu anlamda, bankacılık sisteminin sermaye yeterliliğinin korunması gerekmektedir. Aksi halde, yani tamamen sermaye oranları

üzerine yoğunlaşmak, bankaları dışsal şokların ardından sermaye yeterlilik oranlarını sağlamak amacıyla bilançolarını küçültmeye teşvik etmekte ve bu ise kredi kıtlığını yaşanmasına yol açmaktadır.

- Bu nedenle, stres testi çalışmalarında bankaların bilanço küçültme faaliyetlerinin, aşırı düşük fiyatlardan varlık satışlarının ve yükümlülüklerindeki değişikliklerin dikkate alınmasında yarar bulunmaktadır.
- Makro ihtiyati izleme çalışmalarına, sermaye gereksinimlerinin yanı sıra likidite kurallarının da dahil edilmesi önemlidir.

Tezde, kredi riskine yönelik makro stres testi gerçekleştirmek üzere bir model dizisi tanıtılmaktadır. Sanayi üretim endeksi, tüketici fiyatları endeksi, bankalararası gecelik faiz oranı ve bankacılık sektörü toplam kredilerinden oluşan makroekonomik ve makrofinansal değişkenlere ilişkin öngörüde bulunabilmek amacıyla doğrusal ve doğrusal olmayan VAR modelleri kullanılmaktadır. Ardından, söz konusu modellerden elde edilen öngörü değerleri dikkate alınarak, panel veri modelleri ile bankacılık sektörü kredi riskinin bir ölçütü olarak tahsili gecikmiş alacaklar tahmin edilmektedir. Tahsili gecikmiş alacakların tahmin ve gerçekleşen değerleri karşılaştırılarak ise ortalama hata kareleri karekökü ve ortalama mutlak hata yüzdesi gibi ölçütler aracılığıyla hangi panel veri modelinin daha iyi kredi riski tahmininde bulunduğu belirlenmektedir. Aynı zamanda, söz konusu yaklaşım kullanılarak, hangi VAR modelinden daha doğru öngörü değerleri elde edildiğini ve dolayısıyla, doğrusal mı yoksa doğrusal olmayan bir VAR modeli kullanılmasının daha uygun olacağını belirlemek mümkün olmaktadır. Bu nedenle, doğrusal ve doğrusal olmayan VAR modelleri arasındaki seçim kararı, modellerin en doğru öngörü değeri sağlama konusunda göstermiş oldukları başarıma göre yapılmaktadır. Sonuçta, esas olarak makro göstergelere ilişkin öngörü değerleri ile ilgilendiğimizden, en iyi VAR modelini belirlemeye çalışmak yerine makroekonomik ve makrofinansal değişkenlere ilişkin en doğru öngörüyü veren modelin belirlenmesi amaçlanmaktadır.

Ampirik bulgular doğrusal olmayan VAR ve panel veri modellerinin daha iyi başarım gösterdiğini ortaya koymakta ve modelleme konusundaki ihtiyatlı yaklaşımımızı doğrulamaktadır. Söz konusu durum, doğrusal olmayan veri oluşum süreçlerini göz ardı eden yazındaki çalışmaların güvenilir ve doğru tahminler ve çıktılar üretme konusunda yetersizliğine işaret etmektedir.

Söz konusu tez ile yazına şu hususlarda katkı yapılması amaçlanmaktadır. İlk olarak, makroekonomik ve makrofinansal zaman serilerinin doğrusal olmayan özelliklerini ele alan çalışmalar bulunmasına karşın, söz konusu çalışma, bankacılık sektörüne yönelik makro stres testi uygulamasında bütünleşik bir biçimde doğrusal olmayan ekonometrik yöntemler kullanan ilk çalışmadır. İkinci olarak, ikinci bölümde tartışıldığı üzere, birkaç istisna dışında yazında makro stres testi çalışmalarında ya VAR ya da panel veri yaklaşımı benimsenmektedir. Türkiye'de stres testi üzerine mevcut çalışmalar değerlendirildiğinde, Türk bankacılık sektörünün dayanıklılığını test etmek üzere VAR ve panel veri modelleri bu çalışma ile ilk kez bir arada kullanılmaktadır. Üçüncü olarak, yaklaşımları birleştirmenin yanı sıra, yazında ilk kez söz konusu çalışma ile hem VAR hem de panel veri modellerinde doğrusal olmayan bir yapı tercih edilmiştir.

Yazın taraması sonucu elde edilen bir diğer önemli bulgu ise makroekonomik modelleme üzerine ve dışsal şoklar sonucunda bankacılık sektöründe oluşan gerilimi ölçme amacına yönelik hazırlanan çalışmaların genellikle doğrusal modeller kullanmış olmasıdır. Bununla birlikte, makroekonomik ve makrofinansal değişkenlerin önemli bir bölümü kısmen de olsa doğrusal olmayan özellik taşımaktadır. Neftçi (1984), Hamilton (1989), Sichel (1993), Terasvirta ve Anderson (1992) ile Öcal ve Osborne'nun (2000) da yer aldığı bir dizi çalışma, çoğu makroekonomik zaman serisinin iktisadi çevrimlerin farlı evrelerinde bakışımsız seyir izlediğini ve doğrusal olmayan bir dinamik sergilediğini ortaya koymuştur. Dolayısıyla, bir iktisadi kriz esnasında makroekonomik değişkenlerin hızlı düşüş gösterdiği ancak toparlanma dönemlerinde aynı hızda yükseliş kaydetmediğine ilişkin bulgular yazında net bir biçimde ortaya konmuştur.

Finansal sisteme ilişkin doğrusal olmayan özellik ve hususların değerlendirilmesi ise yazında yakın zamanda sıklıkla ele alınan bir konu olup, özellikle son küresel krizin ardından yaygın bir şekilde işlenmeye başlamıştır. Yapılan analizlerden elde edilen bulgulara göre, finansal sistem bir ölçüde doğrusal olmayan bir dinamik sergilemektedir. Söz konusu durum ise büyük ölçüde finansal sistemi oluşturan piyasa ve kuruluşların birbiriyle olan bağlantılılığı nedeniyle bir noktada ortaya çıkan riskin yayılma özelliği göstermesi ve olumsuz dışsallıklar görülmesi sonucu ortaya çıkmaktadır. Örneğin yüksek kaldıraç oranı ile çalışan ve aşırı risk alan bir kuruluşun finansal koşulların bozulduğu dönemlerde varlıklarını yok pahasına satması, diğer finansal kuruluşlar ve sistemin bütünü üzerinde olumsuz dışsallıklar yaratabilmektedir (Adrian ve Brunnermeier, 2011). Ayrıca, bir bankanın iflası, bankalararası piyasalar ile ödeme ve takas sistemleri aracılığıyla bankalar arasında gözlemlenen bağlantılılık nedeniyle finansal sistemde bir sirayet etkisi yaratarak olumsuz dışsallıklara yol açabilmektedir (Acharya, 2009). Bunun bir sonucu olarak, iflas olasılığı düşünüldüğünde bir bankanın sistemik riske katkısı doğrusal olmakla birlikte, kuruluşun büyüklüğü ve portföyünde yer alan varlıkların karşılıklı ilişkisi dikkate alındığında bu katkı doğrusal olmayan bir özellik kazanmaktadır (Huang et al, 2011). Bu nedenle, son küresel krizde de açıkça görüldüğü üzere, finansal sistemin sağlıklı konumdan çıkarak bir gerilime sürüklenmesi doğrusal olmayan bir biçimde gerçekleşebilmektedir.

Bununla birlikte, bankacılık sektörünü bir makro stres teste tabi tutmak üzere bir VAR ya da panel veri yaklaşımı benimseyen ve yahut iki yaklaşımı da birleştiren mevcut çalışmalarda makroekonomik ve makrofinansal zaman serilerinin doğrusal olmayan özellikleri genellikle göz ardı edilmektedir. Yazında yer alan çalışmaların aksine, bu çalışma, kullanılan değişkenlerdeki doğrusal olmayan özellikleri dikkate almak üzere doğrusal olmayan VAR ve panel veri modellerinden yararlanmaktadır.

Tez planı aşağıda belirtildiği biçimde oluşmaktadır. İkinci bölümde, VAR ve panel veri modellere ilişkin yazın incelenmektedir. Burada söz konusu modellerden elde edilen bulgular ile söz konusu iki farklı türden modelin birbirine nasıl eklemlendiği tartışılmaktadır. Yazında, bankacılık sektörünün dışsal şoklar karşısındaki kırılganlığını ölçmek üzere kullanılan makro stres testi çalışmalarında, genellikle, ya makroekonomik ve makrofinansal değişenler arasındaki etkileşimleri incelemek amacıyla bir VAR modelin kullanıldığı makro yaklaşım benimsenmekte ya da makro ve mikro göstergelere dayalı olarak bankacılık sektörünün risk profilinin tahmin edilmeye çalışıldığı mikro yaklaşım öne çıkmaktadır.

Bankacılık sektörü ile iktisadi çevrimler arasındaki etkileşime atfedilen önemdeki artışa paralel olarak, reel sektör ile bankacılık sektörü arasındaki etkileşimi modellemeyi, esneklik katsayılarını elde etmeyi amaçlayan çalışmaların sayısı artmıştır. Bankalar, gelecekte karşılaşabilecekleri öngörülebilen ve öngörülemeyen zararları için sermaye tamponu oluşturdukları ve karşılık ayırdıkları için, araştırmalarda genellikle sermaye tamponları, zarar karşılıkları veya tahsili gecikmiş alacakların bizatihi kendisi, GSYİH veya sanayi üretim endeksi gibi göstergelerle temsil edilen iktisadi çevrimlerle ilişkilendirilmeye çalışılmaktadır.

Uygulamada, bankacılık sektörünü stres testine tabi tutmak için gerekli olan senaryolar makroekonomik değişkenlere verilen şoklar kullanılarak kurgulanmakta ve makroekonomik değişkenlere ilişkin projeksiyonlar ise VAR modeller vasıtasıyla oluşturulmaktadır. Bankacılık sektörü bilançosunun iktisadi çevrimlere paralel olarak değişim göstermesi nedeniyle, makroekonomik ve makrofinansal değişkenler arasındaki etkileşimin değerlendirilmesine olanak sağlayan VAR modelleri kullanılarak etkili ve güvenilir tahminler üretilebilmektedir. Bankacılık sistemi ve iktisadi çevrimler arasındaki ilişkiye giderek daha fazla önem atfedilmesi sonucunda, reel kesim ile bankacılık sektörü arasındaki etkileşimi ölçmeyi ve esneklikleri elde etmeyi amaçlayan model çalışmalarına olan ilgi artmış ve bu alanda yapılan çalışma sayısı hızla artmıştır. VAR modelleri kullanılarak makroekonomik ve makrofinansal değişkenler arasındaki etkileşim incelenmekte ve geri beslemeler ölçülmekte iken, panel veri modelleri ile makro ve bankalara özgü göstergeler vasıtasıyla bankacılık sektörünün risk profili analiz edilebilmektedir. Yazında, varlık kalitesinin bir ölçütü olan tahsili gecikmiş alacaklar ile iktisadi çevrimler arasındaki ilişkiyi değerlendiren çok sayıda çalışma bulunmaktadır.

Uygulamada yer alan çalışmalar değerlendirildiğinde yazının önemli bir bölümünün ya bankacılık sektörü ile reel ekonomi arasındaki başlıca etkileşim kanallarını da kapsayacak bir analizi esas aldığı ya da stres testini tekil kuruluşlar veya bankacılık sektörü üzerinden kurgulayan bir yaklaşım içine girdiği görülmektedir. İkinci durumda, bir makroekonomik senaryo gereksiniminin sıklıkla IMF gibi bir uluslararası kuruluşun ya da bir kamu kuruluşunun (örneğin merkez bankası tarafından kullanılan makroekonomik modelden elde edilen) makroekonomik göstergelere ilişkin öngörüler kullanılarak karşılandığı görülmektedir. Yalnızca birkaç merkez bankasında makro stres testleri makroekonomik senaryoların oluşturulmasını da kapsayacak bir biçimde ayrıntılı bir analiz çerçevesi içinde gerçekleştirilmektedir. Söz konusu yaklaşımı benimseyen merkez bankalarının başında gelen İngiltere Merkez Bankası'nın, sistemik kuruluşların riskliliğini değerlendirmek için kullandığı ve RAMSI adı verilen modeli buna bir örnektir.

Üçüncü bölümde, 2000-2001 krizleri sonrasını kapsayan analiz dönemi esnasında ekonomide ve finansal sistemde yaşanan başlıca gelişmeler ve yapısal değişiklikler ele alınmaktadır. Güçlü Ekonomiye Geçiş Programı'nın uygulamaya konulması ile birlikte, para ve döviz kuru politikalarına ilişkin yeni bir çerçeve benimsenmiştir. Mali disiplin ve fiyat istikrarında gözlemlenen iyileşme faiz hadlerinin düşmesine ve Türk lirasının değer kazanmasına yol açmıştır. İktisadi görünümdeki iyileşme ve dolayısıyla olumlu beklentilerdeki artış sonucu, yatırım ve tüketim kararları daha çekici hale gelmiştir. Ayrıca, finansal piyasalarda istikrarın tesis edilmesi ve makroekonomik belirsizliklerin giderilmesi ile birlikte kredi talebi önemli ölçüde artış göstermiştir. Bankacılık sektörünü yeniden yapılandırmaya yönelik köklü ve kapsamlı tedbirler, sektörün başta reel sektöre kredi sağlanması olmak üzere temel aracılık faaliyetlerine dönmesine imkan sağlamış, dışsal şoklar karşısındaki dayanıklılığını artırmış ve güçlü bir risk yönetimi doğrultusunda kapasitesini geliştirmesine yardımcı olmuştur. Dolayısıyla, değerlendirmeye tabi tutulan dönemde, bankalar reel ekonomiye daha fazla kaynak aktarmasına paralel olarak, bankacılık sektörünün varlık yapısında önemli bir dönüşüm yaşanmıştır.

2007 yılının Ağustos ayında ABD finansal piyasalarında başlayan kriz, 2008'te bir küresel finansal krize dönüşmüş ve Türkiye'de reel ekonomi ve finansal sistem üzerinde olumsuz etkiler yaratmıştır. Diğer taraftan, daha yüksek büyüme öngörülerine sahip olması ve uluslararası fonların küresel piyasalarda daha yüksek getiri arayışına girmesi, Türkiye'nin de aralarında yer aldığı yükselen piyasalara yoğun sermaye girişlerinin yaşanmasına yol açmıştır. Yoğun sermaye girişleri yurt içi kredi hacmini ve dolayısıyla yurt içi talebi besledikçe, bankacılık sektörü toplam kredileri hızlı artış göstermiş ve finansal istikrara ilişkin kaygılar önemli ölçüde artmıştır. Küresel finansal krizin ardından gelen dönemde Türkiye'de finansal ve ekonomik istikrarı korumak amacıyla politika yapıcıların çok daha aktif bir tutum izleyerek olağandışı tedbirlere başvurduğu görülmüştür. Sağlam bir sermaye yapısı ve kârlılık başarımına sahip olan Türk bankacılık sektörü, analiz dönemi süresince, küresel dalgalanmalara ve diğer dışsal şoklara karşı sağlam bir duruş sergilemiştir.

Dördüncü bölümde tezde kullanılan modeller tartışılmaktadır. Kredi riskine ilişkin bir makro stres testi gerçekleştirmek üzere, söz konusu bölümde, bağımsız ancak birbirini tamamlayan bir dizi model tanıtılmaktadır. İlk olarak, reel sektör ile finansal sistem arasındaki etkileşimi değerlendirmek amacıyla makroekonomik ve makrofinansal değişkenler arasındaki ilişkiler incelenmektedir. Birincisi, doğrusal bir VAR model oluşturulmaktadır. Daha sonra, makroekonomik ve makrofinansal serilere içkin olası doğrusal olmayan hususları gözeterek, bir doğrusal olmayan model tanıtılmaktadır. Ardından, bankacılık sektörünün varlık kalitesini belirleyen mikro ve makro göstergeleri saptamak üzere panel veri modeller oluşturulmaktadır. Bunu gerçekleştirmek üzere tahsili gecikmiş alacaklar, bir dizi makroekonomik ve makrofinansal değişken kullanılarak açıklanmaya çalışılmaktadır. Durağan veya devingen ya da doğrusal veya doğrusal olmayan bir nitelik taşımasına göre farklı panel veri modelleri kullanılmaktadır. Bu çerçevede, öncelikle sabit veya rassal etki panel veri modellerini içeren durağan panel veri modelleri dikkate alınmaktadır. Ardından, tahsili gecikmiş alacaklardaki değişkenliği ölçmek üzere bir dinamik panel veri modeli üzerinde durulmaktadır. Daha önce tartışıldığı üzere, finansal göstergelerin doğrusal olmayan nitelikleri dikkate alınarak ise bir doğrusal olmayan panel veri modeli değerlendirmeye alınmaktadır.

Burada temel amacımız, makroekonomik ve makrofinansal değişkenlere verilen şoklar kullanılarak tahsili gecikmiş alacaklara makro stres testi uygulamak ve bir aylık bir zaman dilimi içerisinde gösterecekleri değişimi incelemektir. Bu doğrultuda, VAR model, esas olarak, finansal sisteme dışsal şok teşkil edecek makro senaryoları üretmek için kullanılmaktadır. Bunu gerçekleştirebilmek için VAR model aracılığıyla makroekonomik ve makrofinansal değişkenlere ilişkin öngörüler elde edilmektedir. Böylelikle, VAR modelden elde edilen öngörüler çerçevesinde oluşturulan dışsal şoklar neticesinde kredi riskinin bir ölçütü olan tahsili gecikmiş alacaklar üzerinde oluşacak stresi ölçmek mümkün hale gelmektedir. Bu türden bir yaklaşım içerisinde değerlendirildiğinde, dışsal şoklar nedeniyle tahsili gecikmiş alacaklardaki değişimlerin tahmin edilmesi bakımından en iyi başarımı doğrusal olamayan panel veri modeli gösterdiği görülmektedir.

Beşinci bölümde ampirik modeller, VAR ve panel veri modelleri, ele alınmaktadır. Söz konusu bölümde esas olarak, üçüncü bölümde teknik detayları verilen VAR ve panel veri model sonuçları tartışılmaktadır. Bu bağlamda, bölümün temel amacı, tahsili gecikmiş alacakların tahmin edilmesi ve önerilen senaryolar çerçevesinde Türk bankacılık sektörüne makro stres testi uygulanmasıdır. VAR modeli sonuçları reel sektörün finansal sistem üzerindeki etkilerini ifade eden birincil etkilere ilişkin bir takım anlamlı bulgular sunmaktadır. Aynı zamanda, finansal sistemin reel sektör üzerindeki etkilerini gösteren ikincil etkilere, diğer bir deyişle, geri besleme etkilerine ilişkin de bir ölçüde anlamlı bulgular elde edilmiştir. Makroekonomik ve makrofinansal değişkenlerin doğrusal olmayan özellikleri, gecelik faiz oranları itibarıyla rejim değişiklikleri kapsamında değerlendirilmektedir. Tezde analiz yapılan dönem esas olarak Türkiye'de enflasyon rejiminin uygulandığı döneme denk gelmektedir. Kısa vadeli faiz oranlarının, söz konusu analiz döneminde, temel para politikası aracı olarak kullanılıyor olması, rejim değişikliklerinde faiz oranlarının belirleyici olduğuna işaret eden doğrusal olmayan test sonuçlarını teyit eder niteliktedir.

Diğer taraftan, tahmin sonuçlarından elde edilen dikkat çekici bir bulgu, toplam kredilerin faiz esnekliğinin istatiksel olarak anlamlı çıkmamasıdır. Bunun birkaç nedenden ileri geldiği düşünülmektedir. Birincisi, analiz döneminin başlangıcı, 2000-2001 krizlerinin hemen sonrasına ve ekonomik istikrar programının uygulamaya konduğu döneme denk gelmektedir. Söz konusu dönem, bankaların, kamuyu finanse etmek yerine elindeki kaynakların önemli bir bölümünü hanehalkı ve firmalara aktarmaya başladığı ve temel aracılık faaliyetlerine geri döndüğü bir dönemin başlangıcıdır. Bankacılık sektörünün aktif yapısında önemli değişiklikler söz konusudur. Dolayısıyla, kredi arzında ciddi bir artış yaşanmaktadır. İktisadi görünümdeki toparlanma ve finansal istikrarın tesisi de, kriz nedeniyle ertelenen yatırım ve tüketim harcamalarında ve dolayısıyla kredi talebinde hatırı sayılır bir artışa yol açmıştır. Bu nedenle, yapısal değişiklikler ile finansal piyasalardaki derinleşmenin kredinin faiz esnekliği üzerinde belirli bir ölçüde etkili olduğu düşünülmektedir.

Faiz esnekliğinin düşüklüğü, ikinci olarak, büyük ölçüde, küresel finansal krizin ardından gelişmiş ülke merkez bankalarının aldığı olağanüstü istikrar tedbirlerinin dolaylı bir sonucu olarak karşımıza çıkmaktadır. Küresel piyasalarda likiditenin bollaşması, yatırımcıların getiri arayışıyla daha yüksek büyüme potansiyeline sahip yükselen piyasalara yönelmesini ve bu ülkelere ait varlık gruplarına olan talebinin önemli ölçüde artmasına neden olmuştur. Türk bankacılık sektörünün yurt dışı kaynaklara ucuz maliyetle ve rahatlıkla erişim sağladığı bu dönemde, küresel likiditenin yurt içi kredi hacmindeki hızla artışta belirleyici olduğu görülmüştür.

Panel veri modelleri bankaların varlık kalitesinin belirleyicilerini saptamada etkin bir biçimde kullanılabilmektedir. Ampirik bulgular, bu çerçevede, makro göstergeler ile bankaların risk profilleri arasında anlamlı etkileşimler olduğunu teyit etmektedir. Bu çerçevede, bazı makroekonomik değişkenler ve bankalara özgü göstergeler bankaların varlık kalitesini açıklanmasında iyi bir başarım göstermektedir. Bu çalışmada, sanayi üretim endeksi, enflasyon, kısa vadeli faiz oranları, toplam kredi hacmi, EMBI gibi makro göstergeler ile kârlılık ve kaldıraç oranı gibi mikro göstergelerin bankacılık sektörünün tahsili gecikmiş alacakları üzerinde belirleyici olduğu gösterilmektedir. Ayrıca, doğrusal olmayan VAR model için olduğu gibi, doğrusal olmayan sabit etkiler panel veri modelinde de test sonuçları, gecelik faiz oranlarının en anlamlı rejim geçiş değişkeni olduğunu göstermektedir.

Özetlemek gerekirse, VAR model esas alınarak oluşturulan makro analiz çerçevesi kullanılarak makro senaryoların oluşturulması ve söz konusu senaryoların ise makro şokların bankaların varlık kalitesi üzerindeki etkilerini değerlendirmek üzere kullanılması hedeflenmektedir. Bu amaca yönelik olarak VAR model kullanılarak makroekonomik ve makrofinansal değişkenlere ilişkin öngörülerde bulunulmaktadır. Ardından, makroekonomik ve makrofinansal değişkenlere ilişkin elde edilen öngörü değerleri ve bankalara özgü göstergeler ile bir sonraki dönem için tahsili gecikmiş alacak değerleri hesaplanmaktadır. Hesaplamalarda kullanılan esneklik değerlerinin elde edilmesinde doğrusal sabit etkiler, rassal etkiler ve devingen panel veri ile doğrusal olmayan panel veri modellerinden yararlanılmaktadır. Makro göstergelere ilişkin öngörü değerlerinin elde edilmesinde en iyi başarımı gösteren modelin doğrusal olmayan VAR model ve bankaların tahsili gecikmiş alacaklarının tahmin edilmesinde en iyi başarımı gösteren modelin ise doğrusal olmayan sabit etkiler panel veri modeli olduğu görülmektedir. Söz konusu bulgu, doğrusal olmayan veri oluşum süreçlerini göz ardı eden önceki çalışmaların yetersizliğini ortaya koyması bakımından oldukça önem taşımaktadır. Hatırlatmakta yarar bulunan bir husus, temel alınacak model belirlenirken, diğer bir deyişle, doğrusal ve doğrusal olmayan modeller arasında seçim yaparken, hangi modelin en iyi olduğu konusunda bir karara varılmamaktadır. Onun yerine, doğrusal ve doğrusal olmayan modellere ilişkin verilen karar, yerine göre makro göstergeleri öngörmede ya da mikro göstergeleri tahmin etmede gösterdikleri başarım değerlendirilerek verilmektedir.

Son olarak, Türk bankacılık sektörünün dışsal şoklara karşı dayanıklılığını test etmek üzere, makroekonomik ve makrofinansal değişkenlere verilen şoklar kullanılarak iki senaryo oluşturulmaktadır. İlk senaryoda sanayi üretim endeksine verilen bir şok değerlendirilmekte ve ikinci senaryoda ise kredi büyümesinin aniden son vermesi durumu göz önüne alınmaktadır. Ardından, kredi riski ile ölçülen varlık kalitesindeki bozulma ile sermaye yeterlilik oranlarındaki değişim hesaplanmaktadır. Elde edilen sonuçlara göre oluşturulan senaryolar çerçevesinde Türk bankacılık sektörü gerek aktif kalitesi gerek sermaye yeterliliği bakımından dışsal şoklara karşı dayanıklı bir görünüm sergilemektedir.

Sonuç olarak, bu çalışma makro stres testi analizinde doğrusal olmayan bir yaklaşım benimseyen ilk çalışmadır. Makroekonomik ve makrofinansal değişkenlerin doğrusal olmayan niteliklere sahip olması ve reel ekonomi ile bankacılık sektörü arasındaki etkileşimin doğrusal olmayan özellikler sergilemesi, makro stres testi çalışmalarında özellikle dikkate alınması gereken hususlar arasında yer almaktadır. Son küresel kriz, risklerin oluşmasında ve tetikleyici unsurların varlığında bir krize dönüşmesinde, yukarıda bahsedilen doğrusal olmayan unsurlar da dahil olmak üzere, sistemik riskin önemini belirgin bir biçimde göstermiştir.

Son küresel krizin açıkça ortaya koyduğu gibi, finansal istikrara yönelik tehditler, kuruluşlar ve piyasalar arasındaki bağlantılılık dikkate alındığında sistemik bir karakter taşımaktadır. Aynı zamanda, sistemik özelliğe sahip krizler, ekonomi ve finansal sistem üzerinde önemli ölçüde tahribatta bulunabilmekte, kamu maliyesine ciddi maliyetler yüklemekte, sosyal ve iş yaşamı üzerinde olumsuz etkiler yaratmaktadır. Bu durum ise politika yapıcıların faal davranarak zamanında tedbirler almasını gerektirmektedir. Söz konusu kararların sağlıklı bir biçimde alınabilmesi ise sistemik riskin değerlendirilmesi, saptanması ve önlenmesine olanak verecek bir tam kapsamlı risk izleme çerçevesinin oluşturulmasına bağlı bulunmaktadır. Bu analiz setinin bir parçası olan makro stres testi çalışmalarında, bu kapsamda, doğrusal olmayan modellere yer verilmesi, finansal istikrarı korumaya yönelik makro ihtiyati tedbirlerin zamanında ve doğru bir biçimde açısından oldukça önemlidir.

APPENDIX D: Curriculum Vitae

PERSONAL INFORMATION

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EDUCATION

Degree	Institution	Year of Graduation
MA	Binghamton University Economics	2004
BS	Ankara University Faculty of Political Sciences Public Finance	1996
High School	Atatürk High School, Ankara	1991

WORK EXPERIENCE

Year	Place	Enrollment
1998- Present	Central Bank of the Republic of Turkey	Specialist

FOREIGN LANGUAGES

English (Fluent), Italian (Basic)

PUBLICATIONS

IRC Expert Group (2014). Report on financial stability challenges in EU candidate and potential candidate countries, European Central Bank Occasional Paper, *forthcoming*.

Karahan, Gülfem and Çakmak, B. (2011). Developments in credit card sector in Turkey. In Ahmet Faruk Aysan (Eds.), *Credit card sector: Questions, challenges* (pp. 31-59). Ankara: Central Bank of the Republic of Turkey.

Çakmak, Bahadır (2006). An early warning system for Turkey. (Promotion thesis, the Central Bank of the Republic of Turkey, Ankara).