# MACRO STRESS TESTING ON THE CREDIT RISK OF THE BANKING SECTOR IN TURKEY

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# MACRO STRESS TESTING ON THE CREDIT RISK OF THE BANKING SECTOR IN TURKEY

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Macro Stress Testing on the Credit Risk of the Banking Sector in Turkey

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DECLARATION OF ORIGINALITY

I, Baurzhan Toktabekov, certify that

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- this thesis contains no material that has been submitted or accepted for a degree or diploma in any other educational institution;
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ABSTRACT

Macro Stress Testing on the Credit Risk of the Banking Sector in Turkey

In our thesis research we conduct a stress test of banking sector in Turkey. Firstly, we develop a model where we regress total and sectoral NPL rates on their lags and macroeconomic indicators. By using the results of the regression we conduct stress tests. As stress test scenarios we use 3 cases. We analyze how the NPL rates of Turkish banking sector would respond to the 2001 and 2008 crisis scenarios and we also look at baseline scenario based on the expectation of OECD on Turkish economy. Based on the results of stress test, not all of the banks in Turkey meet the capital adequacy ratio requirement and under the 2008 crisis scenario total NPL rates rise up to 6.07%. Our sectoral regressions suggest that while our macroeconomic variables are all significant in defining the total NPL rates, some sectoral NPL rates do not necessarily depend on all of them.

# ÖZET

## Türkiye Bankacılık Sektörü Kredi Riskinin Makro Stres Testi

Tez çalışmamızda Türkiye Bankacılık sektörüne kredi riskine stres testi uygulamaktayız. İlk olarak, genel ve sektörel takipteki kredi oranlarını kendi gecikmelerinde ve makroekonomik veriler üzerinde regresyon yaparak model oluşturmaktayız. Regresyon sonuçlarını kullanarak modelimize stres testi uygulamaktayız. Stres test için 3 adet farklı senaryo uygulanmaktadır. Çalışmamızda Türkiye bankacılık sektörünün 2001 ve 2008 kriz senaryolarından ve OECD ve Merkez Bankası beklentilerinden oluşturulan temel senaryodan nasıl etkileneceğini incelemekteyiz. Test sonuçlarına göre bazı banka sermayelerinin talep edilen sermaye yeterlilik oranının altına düştüğü ve 2008 kriz senaryosunda toplam takipteki kredi oranın 6.07% seviyesine yükseldiği görülmüştür. Sektörel kredi regresyon sonuçları kullanmış olduğumuz tüm değişkenlerin takipteki kredi oranlarını etkilemekle beraber, her sektörün tüm değişkenlere bağlı olmadığı görülmüştür.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

# CHAPTER 1

# INTRODUCTION

As the international trade grows and financial systems are becoming more intertwined today, the importance of financial soundness and resilience grow larger. Predicting, preparing and taking precautions against unexpected shocks in order to adjust in timely manner can help economies to face and overcome them in least disruptive ways. Early warning systems and calculation of the effect of a probable collapse could serve as a good tool to take necessary precautions and avoid crises by detecting early signals. Most of the developing countries have been going through financial turmoil in the 1990s and early 2000s, as their financial systems were not ready to withstand the external pressure. Countries started to apply structural adjustment packages and macro stress testing has started to be applied as a tool to understand the soundness of their financial systems. It has been used since early 1990s and started to be widely used after the adoption of financial sector assessment program by IMF and World Bank at the end of 1990s.

The FSAP had the objective to assess the stability of financial system and evaluate the potentials of growth. Some of the actions under the first objective included the evaluation of the resilience of the banking and non-bank financial sectors, stress testing and analysis of systemic risks among banks and other institutions with the emphasis of domestic and external vulnerabilities, assessment of the ability of taken precautions to absorb the effects of possible shocks. The program has been revised in 2009 in response to the global financial crisis and changes were made in the stability assessments and Risk Assessment Matrices along with modular FSAPs were introduced.

Stress testing has been one of the major components of the program since its beginning. According to Blaschke, Jones, Majnoni and Peria(2001) it can be defined as a range of techniques used to assess the vulnerability of a portfolio to major changes in the macroeconomic environment or to exceptional, but plausible events. Since its introduction the tool has been widely applied by the Central Banks and international institutions to test resilience of financial systems of countries and by banks to understand their own riskiness and overall positions.

Similarly, to many emerging market economies Turkish financial sector has experienced a lot of turmoil in the recent past. The crises of 1990s and the steps taken afterwards were not successful in transforming the system' resilience and it was hit by a more severe blow in 2001. As the importance of financial stability has become obvious, Turkey implemented strict policies in its control of the financial sector. The structural adjustments have begun as early as 1999 under the supervision by IMF and World Bank in the scope of FSAP. However, Turkish financial system has not adjusted itself properly, and the additional pressure stemming from the insistence on controlled exchange rates by the IMF and World Bank have led to severe crisis in 2001. Nevertheless, with the recommendation and supervision by the two organizations Turkish financial system continued its adjustments and reformation after the crisis. An independent organization BRSA was founded to control the developments and the risk appetite of banks in the country. Banking and financial systems have dramatically changed since then and as a result 2008 crisis has had relatively less severe effects on the Turkish financial sector, even though the country has experienced one of the largest decreases in GDP level in the World. Overall, the economic history has shown that financial stability is crucial for the stability of Turkish economy, as it has been sensitive to shocks in financial system and due to this fact, it has experienced hard times in the recent past.

In our study we perform a stress-test analysis of the credit risk of banking sector in Turkey to understand how well the Turkish banking system is positioned, how it will respond to external shocks and what has changed since the last two crises. Our model is based on the integrated approach model developed by Wilson in 1997, where he regresses the default rates on different macroeconomic variables. Since the sole regression of default rate on macroeconomic variables led to controversial results we have also added a lag of the dependent variable, which yielded more plausible results. In our analysis as a macro stress-test scenarios, we developed a baseline scenario and an adverse scenario based on historical approach in order to test the resilience of the exposure of credit risk of banking sector. Adverse scenarios are derived from historical data and based on the performance of the Turkish economy and banking system during the 2008 and 2001 crises, while the baseline scenario is based on the forecast of the Turkish economy by OECD for 2019. In line with the study of Vazquez, Tabak, and Souto (2012) as a first step, in our analysis in order to find out the best model for our regression, we conduct a panel regression using quarterly NPL rates of 18 banks, where we compare pooled OLS, within-group estimation and different variations of GMM model and find that the model that fits our data the best is first difference GMM model with macroeconomic variables taken as exogenous. We then use this model's lag structure to look at how NPL rates of different credit types and NPL rates of banks separately respond to our stress scenarios, where using regression result, we estimate individual banks' future NPL rates using the defined stress test scenarios.

As banks want to be aware of the risks they face and understand own resilience, stress-testing is used to assess the effect of stress scenarios on their capital adequacy ratios. With this reason in mind, we also assess the CAR of banks using the results of stress tests. Calculation of future CAR will help us understand how resilient the banks are individually and if Central Bank needs to take precautions like increasing capital requirements to help them avoid probable default. In all scenarios Turkish banks and the banking system overall seems to be resilient to the shocks, where, even under the most adverse scenario case the 2008 financial crisis, NPL ratio increases up to $6.07\%$. The application of 2008 crisis scenario, however, yields the similar results to the real ones, even though a decade has already passed. In 2008 crisis the banking system of Turkey has shown resilience, but not much has changed since then, despite the argument by IMF about improved FSAP since the last global financial crisis.

My study contributes to the literature by applying macro stress testing to NPL rates by credit types in Turkey, which as argued by Vazquez, Tabak, and Souto (2012) grants NPL rates to be more sensitive to changes in macroeconomic variables. Besides, in my study I use different panel data techniques and apply and compare different GMM models and choose the difference GMM model, with macroeconomic variables taken as endogenously determined, to eliminate the bias from using lag of dependent variable-a method that was not previously used in Wilson-type models applied for the analysis of NPL rates in Turkey. In my study I conduct capital adequacy ratio calculation for each bank separately and find that some of the banks fail to meet required levels. Previous studies on Turkey did not report bank level calculations of CAR and they also reported that banking sectors CAR does not fail in adverse scenario cases.

The rest of the thesis is structured as follows: Chapter 2 summarizes existing literature on macro stress testing model and methodologies and provides example studies, especially on Turkish banking system. Chapter 3 provides the macro stress testing model used in my study with its detailed description and data analysis. Chapter 4 provides the results of the regression for overall banking system, for NPL rates by credit types, discusses the results of stress testing for banks and provides calculation of their CAR in each scenario. Chapter 5 shows the regression results using ARDL model. Chapter 6 draws the conclusion of my study. Some of the detailed tables and graph are given in the appendixes.

# CHAPTER 2

# LITERATURE REVIEW

Stress testing has started to be widely applied since the beginning of the implementation of Financial Sector Assessment Program (FSAP) and many Central and private banks have developed their own methods to calculate banks' resilience to shocks. While the individual banks tests at individual level have more detailed data, Central Banks have the advantage of capturing system's overall vulnerabilities. Besides applying top down tests Central Banks can also apply bottom up approach, where they collect the result of the tests run by the individual banks. However, bottom up approach becomes complex when the banks have different methodologies of conducting tests, while applying top down method may result in biased estimation due to lack of detailed data and failure to account for the differences between banks and loans.

The nature and the way stress testing are conducted can vary depending on several objectives and criteria. Blaschke, Jones, Majnoni, and Peria (2001) characterize stress testing as a six-step process. Firstly, in the process the type of risk model is chosen. There are 3 types of risks according to the authors, namely, market risk (interest-rate risk, exchange rate risk), credit risk and other (liquidity, operational). After the risk type is selected the type of stress test is specified (sensitivity, scenario and other) and is followed by shocks such as individual market variables, underlying volatilities and underlying correlations. The shocks can be either historical, hypothetical or created by Monte Carlo simulations. After the scenario is specified one should decide on which of the core assets are to be stressed by how much and on what periods. The last step of the process is the analysis of the risks and adjustment of the present portfolio in line with the upcoming risks.

According to Drehman (2008), stress testing has three objectives: validation, decision making and communication. According to him, methodologies and the models used for testing can vary from each other based on those objectives. Validation refers to checking correctness of the models used by a bank in deciding on capital levels to be hold. Decision making can also depend on the stress test results and similar to validation the requirement for the correctness and accuracy of the stress test model is high. When the object of stress testing is communication, agents aim to reveal the vulnerabilities of the system rather than to calculate the probable future outcomes and the story telling part of the model becomes more important compared to its correctness. According to Drehman the challenges faced by the stress test analysts are data collection and endogeneity of risks. Since the stress testing area is not old enough and the models and methodologies are still in the process of being developed, current data in the field might not be enough and it will take for new data to be collected. Endogeneity risk refers to the endogenous behavior of the agents being tested, who after facing a shock will respond accordingly and change their behavior. The changes in the behavior will make predictions of the outcomes harder for long horizon stress test. Some other problems according to the author are liquidity risk, macro feedback and non-linearities.

## 2.1 Current methodologies

The methodologies for stress testing according to Sorge (2004), can be divided into two main approaches. "The reliance on forecasting models of single financial soundness indicators under stress characterizes the “Piecewise Approach”. In this framework, each indicator (such as non-performing loans or loan-loss provisions) adds potentially useful information for an overall assessment of the vulnerability of the financial sector. A number of other studies have attempted instead to combine the analysis of multiple risk factors into a single estimate of the probability distribution of aggregate losses that could materialize under any given stress scenario. This approach is called as "Integrated Approach".

### 2.1.1 Piecewise approach

In this approach model can be expressed in the following form

$$E(\tilde{Y}_{i,t+1}/\tilde{X}_{t+1} \geq \bar{X}) = f\{X^t, {Z^t}_i\} \tag{2.1}$$

where Y is a vector of variables that are stressed on extreme realization of X and some models can also include a vector of exogenous variables. This model can be estimated as a reduced form regression using panel and time-series data or as a model that analyses resilience of banking sector to fluctuations in macro-fundamentals in economy wide or inter-industry structural models. The latter estimation method outperforms the former in its ability to capture system wide risks and better characterization of stress environment. Both methods are straightforward and simple in explaining, however, this simplicity has a cost of missing out nonlinear relationships between the dependent and independent variables.

### 2.1.2 Integrated approach

In this method all of variables, such as prices, unemployment rates, inflation rates are constructed to form a single estimator of the risk using value-at-risk measure. According to Sorge (2004), moving from a micro to a macro perspective, several studies have recently attempted to develop a similar "integrated approach" for macro stress-testing by incorporating macro fundamentals into value-at-risk measures as following:

VAR_i,t ( _i,t+1/ _t+1$\geq \bar{X}) = f\{E_{i,t}(X_t); P_t(X_t); PD_t(X_t); LGD_t(X_t); \sum_t(X_t)\}$ (2.2)

$$X_t = h(X_{t-1}, ...X_{t-p}) + \epsilon_t \tag{2.3}$$

where Y is vector of variables that are stressed on extreme realizations of X. E is a vector of credit exposures and market positions and is valued at time t based on prices, probability of default, loss given default and a matrix of default volatilities and correlations $\sum$. $X_t$ are the macroeconomic variables that receive shocks through $\epsilon_t$ and in turn affect above mentioned credit quality, prices, probability of default and expected recovery of loans in case of some shock.

The advantage of integrated approach compared to Piecewise Approach is that it allows the integration of market and credit risks and it also allows the estimation of relation between each of the variable in function f(...) and macroeconomic variables X. The latter characteristic of the model could possibly enable avoiding the "ceteris paribus" cases and allow the estimation of change that results from simultaneous fluctuations in variables.

One of models developed under Integrated approach is the model based on Wilson's (1997a-b) study, where the default rates are built conditional on current state of economies and integrate the industry sensitivities. The model uses logistic function and according to Drehman (2005) it is one of the strengths over linear models as the non-linear models suit well in capturing non-linearity of credit risks.

The model is widely used in stress testing literature. Wang, Choi and Fong (2008) in their study conduct a macro stress testing of credit risks of banks in Hong Kong using the model based on Wilson's approach and conclude that even under severe scenarios banks continue to make profits and only under extremely severe scenario only some banks may incur losses. The model is used by Boss (2002), where in his study he finds that default rates in Austrian financial sector could be estimated by macroeconomic variables such as industrial production, unemployment rates and interest rates. As he aims to improve the credit risk model used by Austrian Bank, he also finds that the credit risks can be better explained by logistic and fractional transformation of default rates and the latter one is more sensitive to changes in macroeconomic variables.

### 2.1.3 Other approaches

Other popular methods for stress testing is VAR model which is similar to Wilson's model except the fact that the first one uses Vector Auto Regression model with all variables. There is an extension to VAR model called Structural VAR model which aims to put certain restrictions on covariance of shocks under normal VAR structure. SVAR model can be helpful in understanding the source of changes in VAR and can be used in analysis of low frequency data as it allows inclusion of contemporaneous data. The model is used by Tian and Yang (2011), to analyze the credit risk of commercial banks in China. Even though SVAR model did not fit their data they find that default rates could be captured well by macroeconomic indicators using VAR model.

## 2.2 Empirical results

Vukelic (2011) and Vukic (2014) in their studies test the resilience of credit risk of banking sector in PIIGS and Balkan countries to macroeconomic shocks such as GDP growth, unemployment and inflation rates. Vukelic (2014) conducts the test for Portugal, Ireland, Italy and Spain by using quarterly data from 1998 to 2013. In his model, at first, non-performing loans rates (also defined as default rates) are regressed on long-term interest rate, inflation rate, unemployment rate and GDP growth rate. He found that all the variables are statistically significant in explaining the NPL rate at 10% confidence interval. The calculated coefficients are used to replicate the stress test scenario where he looks at baseline scenario based on OECD's expectations and adverse scenario based on historical approach where he uses worst economic outcomes during 2008 crisis. Lastly, the two scenario results are used to calculate capital changes of the largest banks in each country.

Wezel, Canta and Luy (2014) in their study conduct a stress test on small open economy where they find that in an adverse scenario NPL rates increase sharply, but the capital adequacy ratios still do well thanks to the large buffer applied by private banks. In their model they add one-time lag of NPL rates as an independent variable.

Önder, Damar and Hekimoğlu (2016) test the credit risk of Turkish banking sector by applying satellite model. They create adverse scenario details based on IMF's Turkey FSAP program according to which GDP growth rate is negative in the first period and slows down in the next period, inflation doubles, benchmark interest rate increases up to 20%, unemployment exceeds 12% and USD/TRY reaching 3.6. They found that in adverse scenario case banking sector's CAR will fall strongly, but, nonetheless, it will stay above the minimum level required by the Central Bank.

Bahadır Çakmak (2014) in his study on stress testing framework for the Turkish Banking Sector uses panel data estimation techniques to regress NPL on monthly growth rates of industrial production and total loans, inflation, EMBI, bank leverage, bank profitability, and bank total assets from 2002 to 2012 of 12 largest banks, while in VAR estimation he has used monthly industrial production, consumer price index, interbank overnight deposit rate and total loans of the banking sector for the same period and found that "nonlinear VAR models perform best in forecasting macro indicators and the nonlinear fixed effects panel data model performs best in predicting the nonperforming loans of the banks". He applies the results to estimate the effect of a shock to industrial production and a sudden stop in credit growth separately on nonperforming loans and capital adequacy ratios where in both scenarios he finds that the Turkish banking sector is resilient to these shocks and CAR fall only to 15.6% and 16.1% respectively which is almost two times larger than the required minimum ratio.

# CHAPTER 3

# MODEL AND DATA

## 3.1 Model

Our aim in this study is to assess the effect of shocks to the macroeconomic variables on the stability of the banking sector. In order to assess this, we will be using a slightly modified version of Wilson's model. Nonperforming loan rates, also referred as default rates, will be regressed on their lags and macroeconomic variables with their lags. The coefficients are then used in replication of stress test scenario by substituting the value of given variables for that certain scenario.

In order to capture the relation between NPL and macroeconomic indicators in our study we will be using logarithmic transformation of NPL rates, where:

$$npl_t = \frac{1}{1+e^{-Y_t}} \tag{3.1}$$

which is transformed to

$$ln(\frac{npl_t}{1-npl_t}) = Y_t \tag{3.2}$$

and $Y_t$ is a set of lags of the dependent variable and macroeconomic variables and it can be expressed as

$$Y_t = \beta_0 + \beta_1 ln(\frac{npl_{t-1}}{1-npl_{t-1}}) + \beta_{2i}\sum_{i=0}^{n} X_{2,t-i} + ... + \beta_{ki}\sum_{i=0}^{n} X_{k,t-i} + \epsilon_t \tag{3.3}$$

Since our model includes the lag of the dependent variables estimating it with simple Pooled OLS methods would yield biased results. In order to get unbiased results, we will need to eliminate the bias stemming from the lag of NPL rate. Since we will be using panel data to estimate the relation in the model, we could use within groups estimation method but while it helps to get rid of the bias between NPL rates and its lag, the model will also yield biased results due to the fact that transformed NPL rates and error terms will be correlated. In the next chapter of the thesis, I will be comparing different variations of GMM model to get unbiased results.

## 3.2 Data

In many studies it was shown that the NPL rates could depend on various macroeconomic fundamentals such as GDP growth rate, CPI index, unemployment rates, exchange rates, interest rate, oil prices etc. The range of independent variables can vary depending on the country dynamics and consumer and firm behaviors. The choice of variables may also be guided by the credit segment that is to be stress tested; for example, while NPL rates of loans to manufacturing can depend on exchange rates, import and export barriers, the credit card loans might depend only on unemployment and inflation rates. In our study we try to capture general dynamics of the economy that affect NPL rates and one part of our analysis looks at the NPL rates across fifteen credit types that might depend on a different spectrum of variables; thus, we want our variables to be as general as possible in terms of their effect area. We have regressed NPL rates on its lags, GDP growth rates, interest rates, unemployment rates, CPI and exchange rates and found that for Turkey they depend on GDP growth rates, unemployment rates and exchange rates.

### 3.2.1 Dependent variable

Our dependent variable is the ratio of quarterly non-performing loans of overall Turkish banking system, fifteen different credit segments and eighteen individual banks to total loans and covers the periods from the first quarter of 2005 to third quarter of 2018 for credit segments and from fourth quarter of 2002 to third quarter of 2018 for banks. The data was obtained from the data bank of The Banks Association of Turkey and Banking Regulation and Supervision Agency.

Table 1 provides the summary of NPL rates for the given periods, where the mean of total NPL rates is 3.54% with standard deviation equal to 0.96%, the minimum value is equal to 2.64% and the maximum value reaches 6.01%. From Figure 1 it can be seen that the total NPL rates have been decreasing until the 2008 crisis where it has experienced a sudden increase followed by decrease after the first quarter of 2010.

Our panel data consists of quarterly NPL rates of 18 banks starting from fourth quarter of 2002 to third quarter of 2018. After we define our best model using bank data we will reevaluate the model using NPL rates by credit types to see how NPL rates evolve in different segments. In Table 1 we have also summarized the data for NPL rates by credit types and in Table 2 10 largest banks' NPL rates for which we will be calculating capital adequacy ratios after we stress test the NPL rates.

The Figures 1, Figure 2, and Figure 3 show that like in gross NPL rates at beginning of the sample period NPL rates for all credit types seem to be very volatile followed by a stabilization period and a shock in 2008 and they have stabilized in the last periods. Indeed, they have decreased from 2-digit levels to 1-digit values beginning from the second quarter of 2004 and have again risen to 2-digit values for some credit types during the crisis and have stayed below 10% after the crisis.

While largest banks showed similar trends to total NPL rates smaller banks in group appear to be more volatile. The maximum NPL rates, however, have been reached in public bank and the public banks have the largest volatility compared to other bank types. Average NPL rate is also largest in public banks.

#### 3.2.2 Independent variables

In selection of independent variables, we have tested different combinations of variables. Some data and some periods had to be dropped due to unavailability of data. We have also found that a model similar to the model used by Vukic, where NPL rates are regressed on macroeconomic variables without inclusion of lag of NPL rates could lead to misleading results like increase in GDP growth rate having positive effect on NPL rates. Besides, the R-squared value were much lower compared to the

Table 1. Summary of NPL Rates by Credit Types(%)

| NPL | Mean | Std.Dev | Min | Max |
|---|---|---|---|---|
| Total | 3.54 | 0.90 | 2.64 | 6.01 |
| Tourism | 2.92 | 0.96 | 1.52 | 7.02 |
| Electr. Gas | 0.40 | 0.41 | 0.10 | 2.26 |
| Renting, Realty | 2.97 | 2.14 | 0.93 | 8.79 |
| Mortgage | 0.74 | 0.52 | 0.11 | 2.14 |
| Vehicles | 3.92 | 2.25 | 0.90 | 10.42 |
| Financial Intermediaries | 0.60 | 0.53 | 0.17 | 2.63 |
| Manufacturing | 4.27 | 1.72 | 2.42 | 9.18 |
| Construction | 4.07 | 1.01 | 2.51 | 7.49 |
| Credit Cards | 6.86 | 1.39 | 4.63 | 10.75 |
| Metallurgy | 2.21 | 1.27 | 0.84 | 6.14 |
| Retail | 4.09 | 1.30 | 2.68 | 8.32 |
| Agriculture | 3.33 | 0.88 | 2.22 | 5.85 |
| Textile | 7.96 | 4.31 | 2.39 | 14.20 |
| Other | 8.65 | 3.23 | 3.87 | 17.03 |

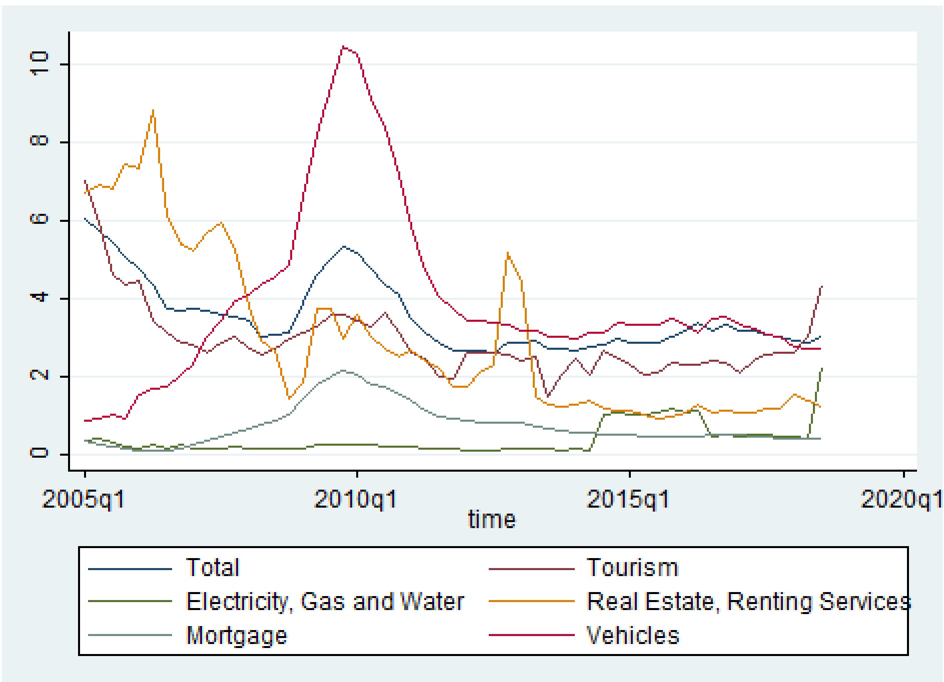


Figure 1. NPL rates by credit types

Table 2. Summary of NPL Rates of Banks and Bank Types(%)

| NPL | Mean | Std.Dev | Min | Max |
|---|---|---|---|---|
| B1 | 6.69 | 14.45 | 1.21 | 60.85 |
| B2 | 4.74 | 3.98 | 1.54 | 18.09 |
| B3 | 3.07 | 1.11 | 1.83 | 6.64 |
| B4 | 2.13 | 0.72 | 1.21 | 4.49 |
| B5 | 5.64 | 2.36 | 3.02 | 11.93 |
| B6 | 7.18 | 6.63 | 2.72 | 32.01 |
| B7 | 12.95 | 20.54 | 2.65 | 95.29 |
| B8 | 5.29 | 2.06 | 2.09 | 10.14 |
| B9 | 4.40 | 1.41 | 2.23 | 8.60 |
| B10 | 2.42 | 0.97 | 0.86 | 5.13 |
| Public | 8.94 | 13.65 | 2.64 | 62.71 |
| Private | 4.02 | 1.50 | 2.08 | 8.11 |
| Foreign | 4.33 | 2.02 | 2.28 | 14.81 |

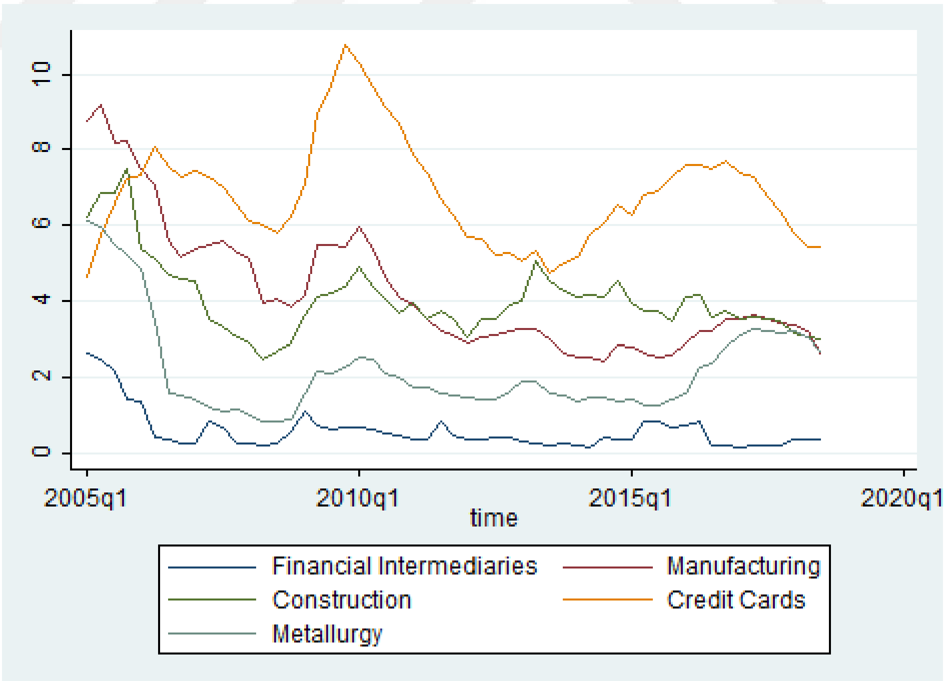


Figure 2. NPL rates by credit types

final model we have used in our study. So, final model, apart from macroeconomic variables includes lag of NPL rates as an independent variable. Inclusion of one lag of

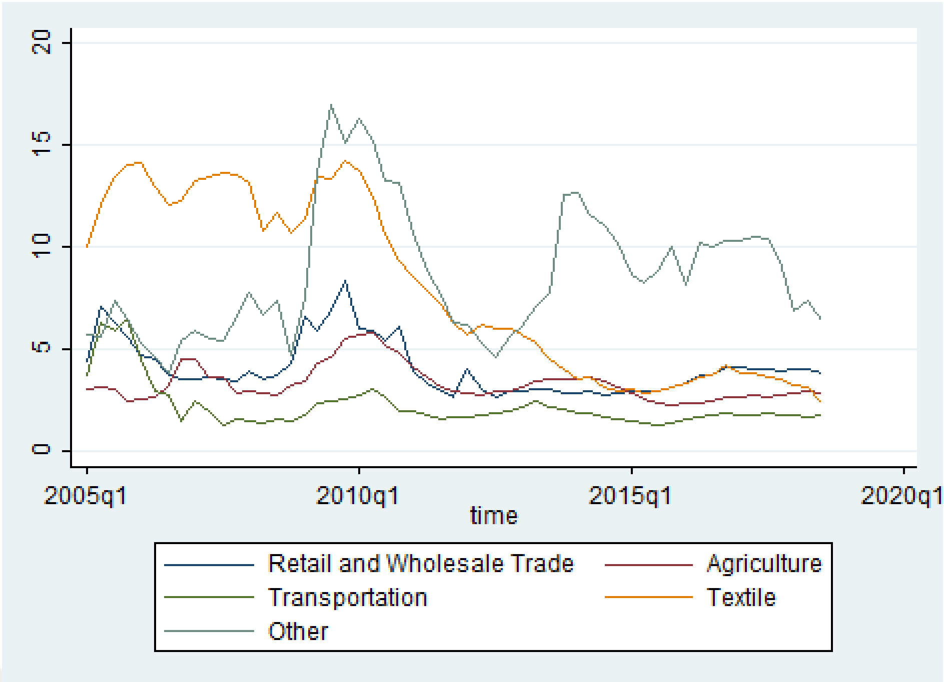


Figure 3. NPL rates by credit types

NPL rates solved contradictory results we obtained earlier and at the same time increased the significance of other independent variables. Similar to model used by Wezel et al. (2014) and Vazquez et al.(2012) our model includes 1-time lag of logistically transformed NPL rates, GDP growth rates, unemployment rates, exchange rates and the lags of these macroeconomic variables.

#### 3.2.2.1 Lag of NPL

The NPL rates are persistent and display strong auto-regressive characteristics as inclusion of lags of NPL rates heavily changes the regression results to more comprehensive and expected ones. In order to include these dynamics of the NPL rates we have included 1-time lag of logistic transformation of dependent variable. i.e.

$$ln(\frac{npl_{t-1}}{1-npl_{t-1}}) \tag{3.4}$$

Obviously, we would expect a positive relation between NPL rates and it is lag, meaning the bigger the NPL rates in the previous period the bigger it will be in the current period. Even though the AR(1) process had a strong explanatory power, as

Table 3. Summary of Independent Variables as of Fourth Quarter of 2002

| Variable | Mean | Std.Dev | Min | Max |
|---|---|---|---|---|
| $GDP$ | 0.72 | 2.30 | -5.2 | 5.5 |
| $Unemp$ | 10.65 | 1.62 | 6.25 | 16.12 |
| $FX$ | 4.99 | 10.95 | -11.04 | 51.09 |

the main goal of our study is to estimate an effect of macroeconomic shock, apart from lag of dependent variable, we have included GDP growth rate, unemployment rate and exchange rate.

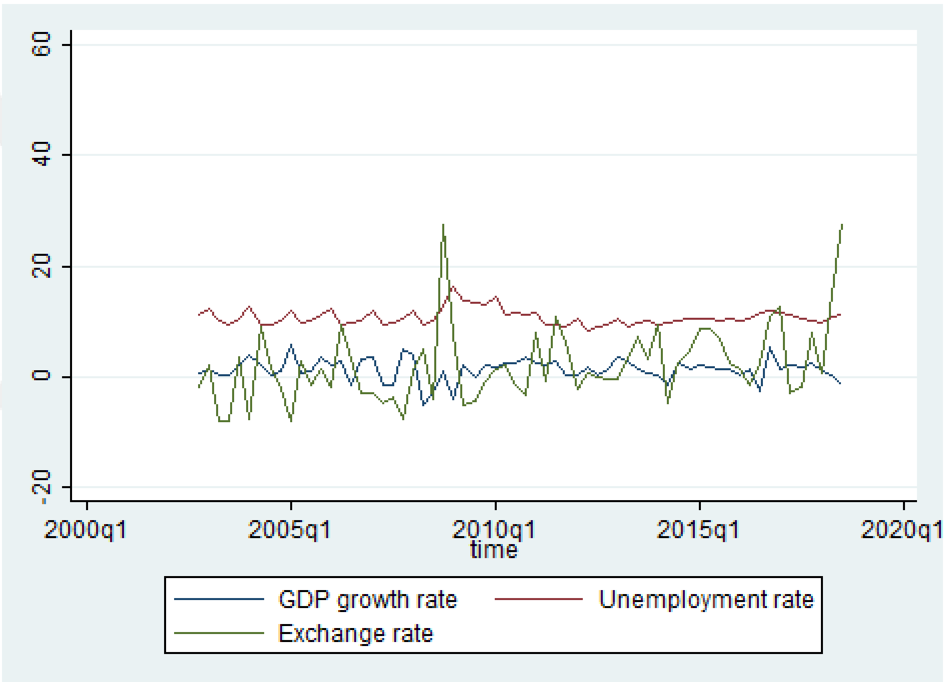


Figure 4. Trends in macroeconomic variables

### 3.2.2.2 GDP growth rate

Following general credit risk modeling tests, we have included seasonally and calendar adjusted quarterly GDP growth rate and its lags calculated as a change as of previous period. As GDP growth rates are correlated with the growth rates of credit volume, we also expect a correlation with NPL rates. Indeed we expect a negative correlation, since as the economies grow and incomes increase, people and firms have more economic power to repay their debts, however, the contrary may also be true, as people may become too optimistic about their future and borrow too much and fail to repay their debts, which will result in growth of NPL rates in the future meaning GDP growth rates' lags can be positively correlated with the dependent variable. The data covers the periods from the fourth quarter of 2002 to third quarter of 2018 and was obtained from the database of Turkish Statistical Institute. During this period Turkish economy on average has grown at $1.41\%$ quarterly, however, the volatility of the growth is very high resulting in drops up to $-5.10\%$ and in increase of $5.50\%$.

#### 3.2.2.3 Unemployment rate

In our model we use seasonally adjusted unemployment rates obtained from the database of Turkish Statistical Institute covering the period from fourth quarter of 2002 to third quarter of 2018. We expect a positive relation between NPL rates and unemployment rates, since as more people become unemployed more people will have financial burden in repaying debts, which will lead to growth of NPL rates. Rising unemployment rates also indicate that firms are having troubles as they are forced to fire their personnel. One of the hardest issues and hot topics in Turkish economy has been unemployment as government has been trapped in controlling unemployment and inflation rates and the employment indicator has stayed above 2-digit levels since the 2002 financial reforms.

#### 3.2.2.4 Exchange rate

One other macroeconomic variable we have included in our model is quarterly change in USD exchange rate. One of the points of critic in recent years has been the inability of Turkish Lira to preserve its strength against USD and its weakening has been linked to weakness of the economy. We wanted to see if it was really the case and how it really affects the performance of the financial system. Intuitively, declining local currency makes local producer against foreigners and drives the exports up; however, on the other side, some companies borrow from banks in foreign exchange rates and weakening local currency means increasing credit risk for those companies. Even though borrowing in foreign currency is not allowed, companies agree with banks to borrow in TRY which is indexed to exchange rate. Overall, changes in exchange rates might drive the borrowing performance up or down depending on the magnitude of change in exports and size of indexed loans. Exchange rates were calculated as a change from previous quarter. The date covers from the fourth quarter of 2002 to third quarter of 2018 and was obtained from the database of Central Bank of Turkey.

In Table 3 we have provided summary of macroeconomic variables used in our model, where "GDP" stands for quarterly GDP growth rate, "Unemp" stands for quarterly unemployment rate and "FX" stands for quarterly change in exchange rate. The summary and the graph of the independent variables depicted in Figure 4 show that they have high volatility especially GDP growth rate and exchange rates. Similar to NPL rates their fluctuation seem to have decreased after 2008 which might be indicative of the causal relation between the dependent and independent variables.

# CHAPTER 4

# REGRESSION RESULTS

In this section we will be providing the results of our estimation. As mentioned previously our data covers periods between fourth quarter of 2002 to third quarter of 2018. We will be separately assessing the NPL rates of total banking sector and fifteen different credit types, then we look at ten banks' NPL rates performances using the same model. Our aim is to assess how banking sector reacts to stress scenarios and also, how granularity of the data yield different results for each credit type.

## 4.1 Estimation method

The model we will be estimating is as following:

$$ln(\frac{npl_{i,t}}{1-npl_{i,t}})=\beta_i + \beta_{1i}ln(\frac{npl_{i,t-1}}{1-npl_{i,t-1}}) + \sum_{s=0}^{q}\beta_{t-s}g_{t-s} + \sum_{s=0}^{r}\beta_{t-s}u_{t-s} + \sum_{s=0}^{s}\beta_{t-s}fx_{t-s} + \epsilon_{t,i} \quad (4.1)$$

Here $npl_t$ stands for the ratio of non-performing loans, in other words loans that are not paid back, to total amount of loans and $npl_{t-1}$ is 1 period lag of those non-performing loans, $g_{t-s}$ stands for seasonally and calendar adjusted quarterly growth rates of GDP at period t-i, $u_{t-s}$ is the unemployment rate at period t-i and $fx_{t-s}$ is the quarterly change in USD exchange rate t-i. The idea behind inclusion of lags of the explanatory variables is that loans do not have to be repaid the moment they are taken, usually they are repaid after a month, a quarter or even a year and there is a legal period for a loan to become non-performing, even if it is not repaid at the repayment date; so, current NPL rates might depend on previous realizations of macroeconomic variables more than today's realizations. For example, in consumer loans 90 days must pass until a bank can call its loan insolvent. Shortly, by including lags of macroeconomic variables we aim to capture the factors that have happened in the past and led to an insolvency of a loan today.

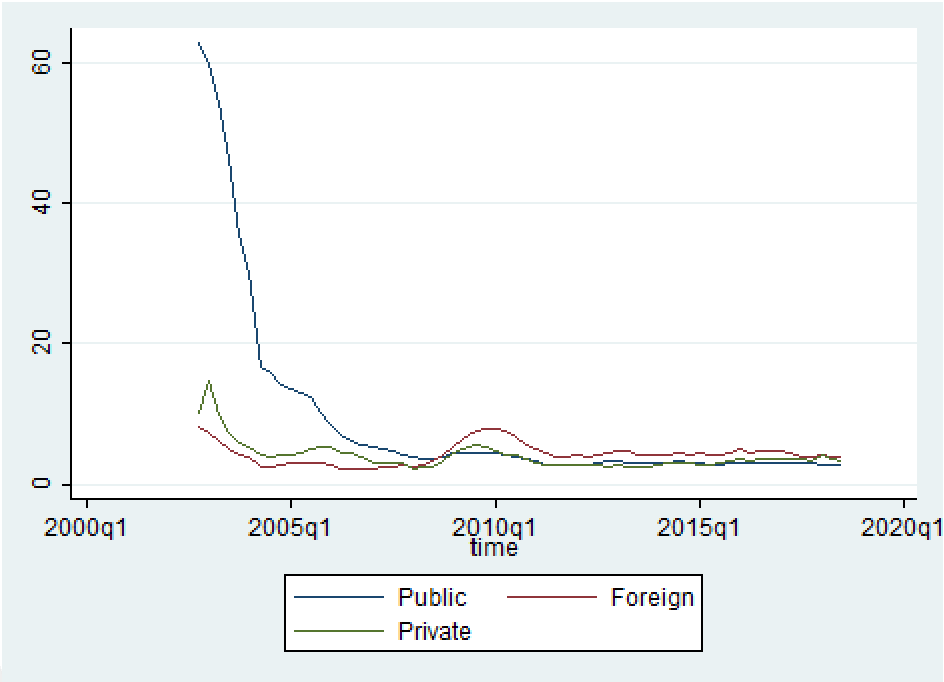


Figure 5. NPL rates by bank types

Since our model includes the lag of the dependent variable among the independent variables, using pooled OLS regression will yield biased results. In order to solve this problem we have followed the study by Vazquez et al. (2012) and have built several models; we similarly have regressed our dependent variable using pooled OLS, within groups estimation and four different variations of GMM model, namely, difference GMM model developed by Arrelano-Bond and system GMM model developed by Arrelano-Bover. For both of the models we look at the cases where GDP growth rates are considered as exogenous or as predetermined. These GMM models solve the estimation bias stemming from the AR(1) process by regressing the first difference form of the original model on the instrumental variables taken from the lags of the exogenous independent variables. The system GMM model is an alternative to the difference GMM model, where the instrumental variables consist of the first differences of independent variables. The alternative aims to solve the problem of inefficiency stemming from unpredictability of the dependent variable and following random walk process. However, the alternative also assumes that the fixed effects between dependent variable and the external independent variables be uncorrelated.

Table 4. Outcomes of Panel Regressions

| | Pooled OLS | Within Groups | Diff. GMM GDP Exog. | Diff. GMM GDP Pred. | Sys. GMM GDP Exog. | Sys. GMM GDP Pred. |
|---|---|---|---|---|---|---|
| $logit(NPL_{t-1})$ | 0.943 (0.000) | 0.915 (0.000) | 0.868 (0.000) | 0.791 (0.000) | 0.868 (0.000) | 0.791 (0.000) |
| $g_t$ | −0.022 (0.000) | −0.022 (0.000) | −0.021 (0.000) | −0.019 (0.000) | −0.021 (0.000) | −0.019 (0.000) |
| $g_{t-1}$ | −0.007 (0.104) | −0.008 (0.089) | −0.011 (0.011) | −0.009 (0.031) | −0.011 (0.011) | −0.009 (0.033) |
| $g_{t-2}$ | −0.008 (0.239) | −0.008 (0.182) | −0.015 (0.006) | −0.011 (0.032) | −0.015 (0.005) | −0.011 (0.034) |
| $g_{t-3}$ | −0.010 (0.077) | 0.009 (0.124) | −0.001 (0.851) | 0.003 (0.611) | −0.001 (0.850) | 0.003 (0.615) |
| $g_{t-4}$ | 0.014 (0.005) | 0.013 (0.011) | 0.003 (0.511) | −0.007 (0.147) | 0.003 (0.508) | 0.007 (0.151) |
| $u_t$ | 0.041 (0.001) | 0.040 (0.001) | 0.028 (0.013) | 0.035 (0.001) | 0.028 (0.012) | 0.035 (0.001) |
| $u_{t-1}$ | −0.001 (0.934) | −0.008 (0.089) | −0.009 (0.265) | 0.000 (1.000) | −0.009 (0.261) | 0.000 (1.000) |
| $u_{t-2}$ | 0.012 (0.136) | −0.001 (0.946) | 0.007 (0.396) | 0.014 (0.069) | 0.007 (0.392) | 0.014 (0.072) |
| $u_{t-3}$ | −0.009 (0.221) | 0.012 (0.126) | −0.004 (0.576) | −0.001 (0.905) | 0.004 (0.573) | −0.001 (0.906) |
| $u_{t-4}$ | −0.024 (0.008) | 0.022 (0.015) | −0.011 (0.199) | −0.012 (0.149) | −0.011 (0.196) | −0.012 (0.152) |
| $fx_t$ | −0.162 (0.002) | −0.153 (0.003) | −0.140 (0.004) | −0.117 (0.016) | −0.140 (0.004) | −0.116 (0.016) |
| $fx_{t-1}$ | −0.033 (0.534) | −0.031 (0.553) | −0.055 (0.265) | −0.024 (0.622) | −0.055 (0.261) | −0.024 (0.625) |
| $fx_{t-2}$ | 0.135 (0.011) | 0.134 (0.012) | 0.099 (0.046) | 0.126 (0.010) | 0.099 (0.044) | 0.126 (0.010) |
| $fx_{t-3}$ | −0.003 (0.946) | 0.001 (0.995) | 0.006 (0.906) | 0.017 (0.719) | 0.006 (0.906) | −0.019 (0.721) |
| $fx_{t-4}$ | 0.274 (0.000) | −0.275 (0.000) | 0.221 (0.000) | 0.275 (0.000) | −0.019 (0.000) | 0.275 (0.000) |
| $Cons$ | −0.401 (0.000) | | | | −0.596 (0.005) | −1.058 (0.000) |
| Obs | 1.080 | 1.080 | 1026 | 1062 | 1044 | 987 |
| $R^2$ | 0.996 | 0.940 | | | | |
| Sargan Test | | | 0.000 | 0.000 | 0.000 | 0.140 |
| AR(1)(p) | | | 0.000 | 0.000 | 0.000 | 0.000 |
| AR(2)(p) | | | 0.000 | 0.000 | 0.000 | 0.001 |
| # of ins. | | | 57 | 59 | 58 | 48 |
| # of banks | | | 18 | 18 | 18 | 18 |

We have estimated our model with different lag structures of independent variables and found that the lag structures presented in Table 4 were statistically significant and best fitted our model in determining NPL rates.

According to the estimation logistic transformation of NPL rates can be explained by their 1-time lag, current GDP growth rate(g) and its four period lags. We also found that it is affected by unemployment rates(u), change in exchange rates(fx) and their four period lags. The results of the estimation show high persistence and robustness across different methods of estimation. Difference GMM method and System GMM method with GDP growth rate, unemployment rate taken as predetermined yield exactly the same results. The signs of the coefficients are all as we were expecting, while for exchange rates short term effect is negative and long-term effects affect NPL rates positively.

Pooled OLS method yields biased estimation since our model includes lag of NPL rates as independent variable. While within group estimation eliminates this bias, it introduces a new bias stemming from the correlation of lag of logistic transformation of NPL and transformed errors. The GMM models help to solve the bias problem stemming from the lag of dependent variable. As a first step the model takes the first difference in order to eliminate possible individual effects. As a second step it deals with the bias stemming correlation between dependent and independent variables that is not eliminated by differencing. In order to get unbiased results, GMM model uses instrument variables generated from the differenced lags of independent variables.

We have taken fourth lags of macroeconomic variables as instruments in IV estimation of GMM model. The results of the models do not differ from each other much apart from the Sargan test probabilities and AR(2) probabilities. Sargan/Hansen test is used to test overall validity of the instruments and the null hypothesis is that all instruments are orthogonal to error terms. The second test examines the null hypothesis that errors terms of the differenced equation are not serially correlated, particularly at the second order. In both GDP treated as exogenous and as predetermined we reject Sargan test at 1% confidence interval and reject AR(2). In our study, we will be using difference GMM model with GDP growth rate taken as predetermined.

Table 5. Outcomes of Regressions by Credit Types

| | Tourism | Electr. Gas | Renting Real Est. | Mortg. | Vehicles | Fin. Interm. | Manuf. |
|---|---|---|---|---|---|---|---|
| $logit(NPL_{t-1})$ | 0.636 (0.000) | 0.878 (0.000) | 0.839 (0.000) | 0.903 (0.000) | 0.853 (0.000) | 0.602 (0.000) | 0.862 (0.000) |
| $g_t$ | −0.019 (0.065) | 0.033 (0.325) | −0.009 (0.623) | −0.019 (0.000) | −0.016 (0.000) | −0.026 (0.436) | 0.006 (0.212) |
| $g_{t-1}$ | −0.028 (0.024) | −0.081 (0.047) | −0.034 (0.102) | −0.017 (0.005) | −0.020 (0.000) | −0.028 (0.456) | −0.012 (0.039) |
| $g_{t-2}$ | −0.012 (0.459) | −0.019 (0.706) | −0.009 (0.728) | −0.026 (0.001) | −0.021 (0.002) | −0.031 (0.532) | −0.010 (0.187) |
| $g_{t-3}$ | 0.002 (0.924) | −0.066 (0.229) | −0.019 (0.516) | −0.017 (0.046) | −0.026 (0.000) | −0.064 (0.232) | −0.005 (0.552) |
| $g_{t-4}$ | 0.005 (0.723) | −0.068 (0.140) | −0.033 (0.175) | −0.001 (0.837) | −0.006 (0.262) | 0.006 (0.901) | −0.001 (0.865) |
| $u_t$ | −0.005 (0.878) | −0.093 (0.403) | −0.031 (0.599) | 0.013 (0.416) | 0.001 (0.937) | −0.031 (0.775) | 0.013 (0.430) |
| $u_{t-1}$ | 0.025 (0.283) | −0.004 (0.960) | 0.038 (0.339) | −0.005 (0.677) | 0.013 (0.130) | −0.032 (0.669) | 0.018 (0.111) |
| $u_{t-2}$ | −0.004 (0.858) | −0.041 (0.574) | −0.024 (0.534) | −0.010 (0.353) | −0.004 (0.635) | 0.044 (0.543) | 0.004 (0.685) |
| $u_{t-3}$ | −0.002 (0.928) | −0.008 (0.906) | −0.040 (0.249) | 0.006 (0.513) | 0.013 (0.091) | 0.014 (0.833) | −0.024 (0.020) |
| $u_{t-4}$ | −0.024 (0.307) | 0.056 (0.476) | 0.062 (0.135) | 0.017 (0.162) | −0.005 (0.623) | 0.039 (0.608) | 0.003 (0.778) |
| $fx_t$ | 0.002 (0.994) | 2.296 (0.023) | −1.109 (0.017) | −0.553 (0.000) | −0.387 (0.001) | 0.745 (0.439) | −0.536 (0.001) |
| $fx_{t-1}$ | −0.270 (0.158) | −0.285 (0.518) | −0.238 (0.344) | 0.188 (0.006) | 0.038 (0.493) | −0.677 (0.156) | −0.196 (0.015) |
| $fx_{t-2}$ | −0.069 (0.703) | 0.235 (0.596) | −0.160 (0.528) | 0.291 (0.000) | 0.026 (0.625) | −0.437 (0.356) | −0.038 (0.629) |
| $fx_{t-3}$ | −0.115 (0.499) | −0.399 (0.406) | −0.371 (0.172) | 0.165 (0.024) | 0.191 (0.001) | −0.438 (0.376) | −0.141 (0.082) |
| $fx_{t-4}$ | −0.199 (0.244) | −0.063 (0.899) | −0.135 (0.630) | 0.251 (0.001) | −0.326 (0.000) | −0.425 (0.394) | 0.073 (0.364) |
| Sargan Test | 0.031 | 0.018 | 0.001 | 0.000 | 0.000 | 0.013 | 0.004 |
| AR(2)(p) | 0.811 | 0.434 | 0.028 | 0.409 | 0.966 | 0.295 | 0.857 |
| Sum of g coef. | -0.003 | -0.013 | -0.007 | -0.005 | -0.006 | -0.010 | -0.001 |
| Long-term effect | -0.010 | -0.110 | -0.043 | -0.055 | -0.040 | -0.024 | -0.010 |
| Sum of u coef. | 0.003 | -0.006 | 0.001 | 0.002 | 0.002 | 0.002 | 0.001 |
| Long-term effect | 0.008 | -0.049 | 0.002 | 0.015 | 0.013 | 0.006 | 0.007 |
| Sum of fx coef | -0.043 | 0.172 | -0.147 | 0.023 | -0.030 | -0.082 | -0.056 |
| Long-term effect | -0.118 | 1.413 | -0.915 | 0.235 | -0.206 | -0.206 | -0.405 |

Table 6. Outcomes of Regressions by Credit Types

| | Constr. | Credit Cards | Metal. | Retail Trade | Agric. | Transp. | Textile | Other |
|---|---|---|---|---|---|---|---|---|
| $logit(NPL_{t-1})$ | 0.887 (0.000) | 0.856 (0.000) | 0.969 (0.000) | 0.358 (0.018) | 0.839 (0.000) | 0.682 (0.000) | 0.954 (0.000) | 0.855 (0.000) |
| $g_t$ | 0.007 (0.395) | −0.001 (0.905) | 0.005 (0.618) | −0.011 (0.199) | −0.002 (0.772) | 0.002 (0.865) | 0.003 (0.534) | 0.022 (0.076) |
| $g_{t-1}$ | −0.009 (0.328) | −0.005 (0.253) | −0.021 (0.052) | 0.002 (0.858) | −0.014 (0.043) | 0.009 (0.524) | −0.015 (0.010) | 0.010 (0.492) |
| $g_{t-2}$ | −0.013 (0.286) | −0.002 (0.768) | −0.005 (0.731) | 0.017 (0.174) | −0.004 (0.627) | −0.003 (0.874) | 0.002 (0.760) | 0.042 (0.029) |
| $g_{t-3}$ | 0.001 (0.931) | 0.002 (0.681) | −0.009 (0.541) | 0.008 (0.567) | −0.016 (0.097) | 0.023 (0.265) | 0.002 (0.762) | 0.034 (0.093) |
| $g_{t-4}$ | 0.004 (0.704) | 0.003 (0.510) | 0.002 (0.895) | 0.030 (0.012) | −0.003 (0.671) | −0.012 (0.488) | 0.014 (0.040) | −0.004 (0.801) |
| $u_t$ | 0.006 (0.810) | 0.022 (0.073) | 0.051 (0.084) | 0.107 (0.000) | 0.003 (0.871) | 0.050 (0.228) | 0.032 (0.053) | 0.147 (0.001) |
| $u_{t-1}$ | 0.003 (0.829) | 0.032 (0.000) | 0.026 (0.188) | 0.039 (0.094) | 0.043 (0.134) | 0.043 (0.134) | 0.015 (0.185) | 0.032 (0.255) |
| $u_{t-2}$ | 0.006 (0.728) | −0.003 (0.720) | −0.048 (0.018) | 0.024 (0.231) | 0.007 (0.568) | 0.009 (0.759) | 0.011 (0.309) | −0.035 (0.221) |
| $u_{t-3}$ | −0.016 (0.309) | 0.005 (0.496) | −0.009 (0.610) | 0.028 (0.098) | 0.014 (0.228) | −0.037 (0.144) | −0.020 (0.048) | −0.018 (0.468) |
| $u_{t-4}$ | 0.001 (0.962) | −0.026 (0.008) | 0.003 (0.899) | −0.098 (0.034) | 0.005 (0.716) | −0.012 (0.689) | −0.016 (0.176) | −0.069 (0.024) |
| $fx_t$ | 0.067 (0.774) | −0.112 (0.316) | −0.479 (0.070) | −0.288 (0.235) | 0.056 (0.751) | −0.529 (0.151) | −0.750 (0.000) | −1.166 (0.002) |
| $fx_{t-1}$ | −0.127 (0.246) | −0.112 (0.037) | 0.008 (0.947) | −0.567 (0.000) | −0.075 (0.344) | −0.534 (0.005) | −0.272 (0.000) | 0.150 (0.362) |
| $fx_{t-2}$ | −0.090 (0.424) | −0.121 (0.019) | −0.032 (0.794) | −0.257 (0.086) | 0.026 (0.746) | −0.326 (0.100) | −0.123 (0.078) | −0.031 (0.851) |
| $fx_{t-3}$ | −0.122 (0.301) | −0.015 (0.771) | −0.062 (0.628) | −0.150 (0.288) | 0.159 (0.068) | −0.344 (0.102) | −0.092 (0.221) | 0.356 (0.048) |
| $fx_{t-4}$ | 0.241 (0.055) | −0.009 (0.863) | 0.222 (0.097) | 0.150 (0.257) | −0.045 (0.610) | 0.192 (0.376) | 0.064 (0.397) | 0.390 (0.038) |
| Sargan Test | 0.070 | 0.000 | 0.000 | 0.053 | 0.000 | 0.078 | 0.001 | 0.026 |
| AR(2)(p) | 0.280 | 0.157 | 0.210 | 0.805 | 0.870 | 0.507 | 0.478 | 0.739 |
| Sum of g coef. | -0.001 | -0.001 | -0.002 | 0.003 | -0.003 | 0.003 | 0.001 | 0.007 |
| Long-tern effect | -0.012 | -0.029 | -0.062 | 0.005 | -0.017 | 0.009 | 0.009 | 0.048 |
| Sum of u coef. | 0.001 | 0.002 | 0.002 | 0.011 | 0.002 | 0.003 | 0.001 | 0.004 |
| Long-tern effect | 0.001 | 0.014 | 0.049 | 0.017 | 0.010 | 0.011 | 0.032 | 0.026 |
| Sum of fx coef. | -0.002 | -0.023 | -0.015 | -0.074 | 0.008 | -0.103 | -0.078 | -0.020 |
| Long-tern effect | -0.018 | -0.162 | -0.468 | -0.115 | 0.050 | -0.322 | -1.698 | -0.138 |

### 4.2 Application of the GMM model

Using above model's lag structure, we have also regressed NPL rates of fifteen credit types. Table 5 and Table 6 shows the detailed regression results. We have chosen credit segments based on their size. Overall these credits account for $77.80\%$ of total credits. The largest credit segment is manufacturing followed by loans to mortgage and loans to construction. Similar to general regression it was found that GDP growth rate and unemployment rate have respectively negative and positive effects on NPL rates. Only in loans to textile and transportation GDP growth rate has positive effects on NPL rates. Unemployment rate affects NPL rates in all of the segments positively except of electricity, gas and water, where its negative effect is not statistically significant. In 12 of the segments exchange rates has negative effects on NPL rates and it is positive in mortgage, electricity, gas and water and agriculture. The results for agriculture are counter-intuitive and only possible explanation could be high dependence of farmers on foreign imports in growing their crop and normally we would expect a better loan performance due to increased demand from abroad caused by depreciation of TRY value. One other similar segment could be manufacturing due to its high dependence on imported intermediary goods, however, increase in exchange rates have negative effect in this segment. Negative effect in textile, retail trade, tourism is expected due to the increased demand from abroad.

Autocorrelation of errors is mostly eliminated by AR(1) specification as majority of autocorrelations of order one fail to reject the null at $5\%$ confidence level and at the second order fail to reject for all credit types in each scenario. At $5\%$ confidence level we fail to reject the Sargan test for loans to tourism, construction, retail trade, transportation and other and for all of the segments STATA reports Sargan tests as "not robust, but not weakened by many instruments".

The lag of NPL rates is strongly significant in all of the credit types and is highest in loans to mortgage, metallurgy and textile and the long run effect of fluctuations in macroeconomic variables on NPL rates are amplified strongly in this credit types even though their short run effects are small. For example, the average

NPL rates of loans to financial intermediaries and mortgage are $0.60\%$ and 0.74% respectively and the short run effect of $100\%$ change in GDP growth rate are equal to $-10\%$ and $-5\%$ change in NPL rates respectively. Even though the short run effect of GDP growth rate on credits to financial intermediaries is larger than on credits to mortgage, the long run effect of GDP growth rate for credit to financial intermediaries is equivalent to $-24\%$, while for mortgage credits it is $-55\%$. Derivation of the short-and-long term effects of changes in macroeconomic variables on NPL rates is given in the appendix A.

## 4.3 Stress testing

The main goal of our study was to look at how NPL rates will evolve in case of a certain shock or, in other words, stress scenario. In this part of the thesis we will introduce the stress test scenarios that will be further used to estimate the possible outcomes caused by them on the NPL rates. Our stress test scenarios involve baseline scenario, that is based on expected values of macroeconomic variables for the last quarter of 2018 for which we exploit the economic forecast for Turkey by OECD and Central Bank of Turkey and on two adverse scenarios based on historic approach, where we look at the greatest shocks the Turkish economy has experienced in the last two decades; one is the Global Crisis in 2008 and the other is the 2001 Financial Crisis.

### 4.3.1 Stress test scenarios

#### 4.3.1.1 Scenario 1: Baseline Scenario

As a baseline scenario we will be stress testing the credit risk based on the future realization of the macroeconomic variables starting from the fourth quarter of 2018 till the fourth quarter of 2019. The data of the forecasts is obtained from OECD's "economic outlook, analysis and forecasts" for Turkey. According to the data the economic growth rate should slow down at the end of 2018 and the Turkish economy will face 0.40% decline in its growth in 2019. Unemployment rate is expected to drop from its peak at the end of 2018 from 13.70% to 12.70%. For exchange rates we have assumed that it will change as prices of goods and have indexed it to CPI. We assume that economy will grow equally in each quarter and, thus, the quarterly expected GDP growth rate is estimated to be equal to -0.10% and the expected quarterly change in FX and its lag estimated to be equal to 5.82%.

#### 4.3.1.2 Scenario 2: 2008 global financial crisis

The most recent and the most relevant shock the banking sector has experienced is the 2008 Global Financial Crisis. Thanks to the reforms and sets of monetary and fiscal policies that Turkey has implemented during and after the 2001 Financial Crisis the dynamics of macroeconomic variables and financial system have become more stable and resilient as it can be seen in overall dynamics of Turkish economy and in how its financial system has reacted to the 2008 crisis. The effects and results of the crisis are included in our data in form of NPL rates and macroeconomic variables, thus, we believe that the result of the stress testing on adverse case scenario based on 2008 crisis shock will be most relevant and illustrative of possible shock and its consequences. The crisis in terms of credit shock has reached its climax in the first quarter of 2009 in which GDP growth rate, unemployment and FX rates have reached -4.0%, 16.12% 7.58% respectively.

#### 4.3.1.3 Scenario 3: 2001 financial crisis

Like many developing economies Turkey has experienced several financial crises in its recent economic history. Due to its severity and its recentness as our second adverse case scenario we chose the 2001 Financial Crisis. The severity of the crisis in terms of credit risk has been reached in the first quarter of 2002 and has decreased then onward as the economy has started to recover in the first quarter of 2002. In the first quarter of 2002 quarterly GDP growth rate, unemployment, FX rates have reached -3.7%, 10.40% 11.04% respectively. The summary of the 3 stress scenarios is given in the Table 7.

Table 7. Summary of Variables for Each Scenario

| Stress variables | Baseline | 2008 Crisis | 2001 Crisis |
|---|---|---|---|
| $g_t$ | -0.10 | -4.00 | -3.70 |
| $g_{t-1}$ | -0.10 | -0.90 | 2.30 |
| $g_{t-2}$ | -0.10 | -3.10 | -5.20 |
| $g_{t-3}$ | -0.10 | -5.10 | -4.50 |
| $g_{t-4}$ | -2.40 | 4.00 | -0.30 |
| $u_t$ | 12.70 | 16.12 | 10.40 |
| $u_{t-1}$ | 12.70 | 12.64 | 7.82 |
| $u_{t-2}$ | 12.70 | 10.18 | 6.73 |
| $u_{t-3}$ | 12.70 | 9.16 | 8.49 |
| $u_{t-4}$ | 13.70 | 11.88 | 6.25 |
| $fx_t$ | 5.82 | 7.58 | -11.04 |
| $fx_{t-1}$ | 5.82 | 27.31 | 9.54 |
| $fx_{t-2}$ | 5.82 | -4.21 | 17.81 |
| $fx_{t-3}$ | 2.03 | 5.06 | 51.09 |
| $fx_{t-4}$ | -1.18 | 0.96 | 15.15 |

### 4.3.2 Credit risk stress testing results

In this subsection we present the results of our estimation of stress test scenarios. We have generated a model for estimation of NPL rates based on Wilson's approach. Since the dependent variable in our model also includes its lag as an independent variable, we have estimated it using different variations of GMM model in order to solves the bias stemming from the lag of NPL rates. Among the 4 variations of GMM model we chose difference GMM model with macroeconomic variables taken as predetermined. According to the model, total NPL rates can be represented as below:

$$\ln(\frac{npl_t}{1-npl_t}) = 0.791 \cdot \ln(\frac{npl_{t-1}}{1-npl_{t-1}}) - 0.019 \cdot g_t - 0.009 \cdot g_{t-1} -$$
$$0.011 \cdot g_{t-2} + 0.003 \cdot g_{t-3} - 0.007 \cdot g_{t-4} + 0.035 \cdot u_t + 0.000 \cdot u_{t-1} +$$
$$0.014 \cdot u_{t-2} - 0.001 \cdot u_{t-3} - 0.012 \cdot u_{t-4} - 0.117 \cdot fx_t - 0.024 \cdot fx_{t-1} +$$
$$0.126 \cdot fx_{t-2} + 0.017 \cdot fx_{t-3} + 0.275 \cdot fx_{t-4} + \epsilon_t \quad (4.2)$$

where $npl_t$ is nonperforming loans rate and $npl_{t-1}$ is its one time lag, $g_t$ is seasonally adjusted quarterly GDP growth rate, $u_t$ is unemployment rate and $fx_t$ is the quarterly change in exchange rates.

Applying the values of the variables from Table 7 to the above specified model yields the estimates of our stress test scenarios. The 2001 financial crisis scenario yielded ambiguous results as the model shows that the NPL rates have suddenly dropped then increased back and followed a sudden drop again. Our data scope used in the estimation of our model does not include the 2001 crisis period and, thus, the model fails to capture the dynamics of that period properly and we expect NPL rates increase only up to $4.14\%$. However, it captures well the 2008 crisis scenario. In 2008 crisis scenario the NPL rates are estimated to grow steadily and reach $6.07\%$. In the baseline scenario we estimate a NPL rates increase up to $5.42\%$. The most severe among the scenarios appears to be the 2008 crisis scenario which is followed by 2001 crisis scenario. The severity of 2008 crisis is in part due to more severe drop in GDP growth rate compared to the 2001 crisis scenario and an increase in unemployment rates. As discussed previously total NPL rates are affected by its lag and GDP growth rates and even though the 2001 crisis has more severe shock on GDP growth rate and exchange rates their effect on NPL rates are driven down by the decrease in unemployment rates.

Figure 6 depicts how NPL rates of NPL rates by bank types evolve in three scenarios. The shocks enter in the fourth quarter of 2018 and lasts five quarters onward. In the graphs each shock has different effects on each bank type. Overall, the public banks are the most exposed to external shocks; while domestic private banks show the dynamics of overall banking system, the foreign banks are affected more than domestic banks. In addition to the difference of bank types based on their ownership, resilience of banks to disturbances might vary based on their asset size as well. The difference between domestic private banks and foreign banks includes difference of their asset size, which might give clues for further research.

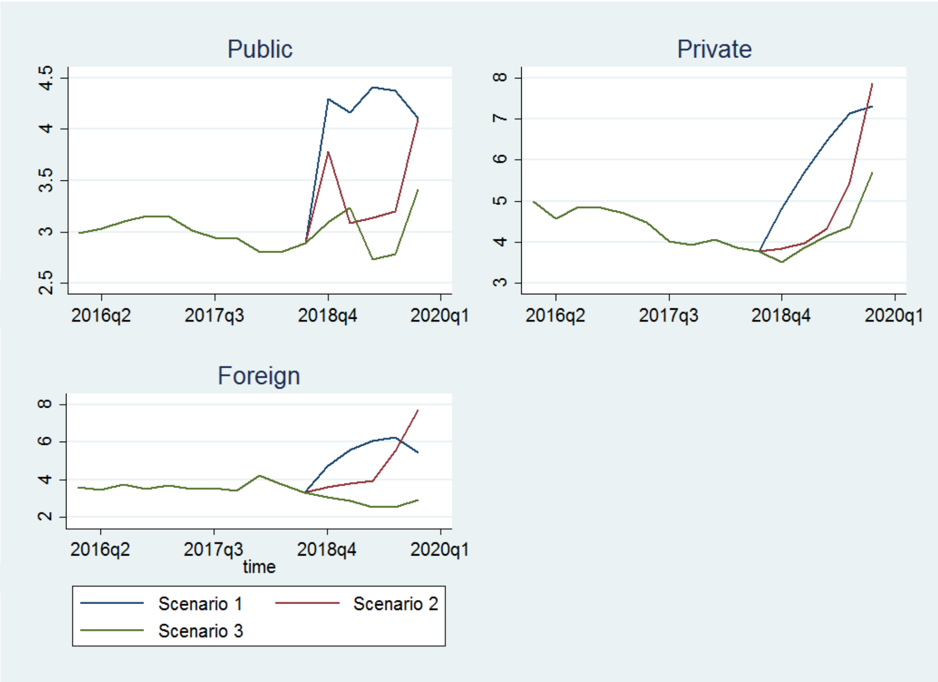


Figure 6. Stress test results

We have also conducted stress test based on credit types, however, some of the results were counterintuitive. For example, NPL rates of loans to electricity gas and water rose up to 38% in 2001 crisis scenario; NPL rates of construction loans dropped compared to initial 2018 third quarter levels, which is not expected in scenarios where economic performance of the country worsens. We have provided the results of stress testing by credit types in the Appendix B.

### 4.3.3 Stress testing of banks' NPL rates

In this section of our study we will be stress testing 10 largest banks based on assets size in Turkey and calculate their capital adequacy ratios using the results of the tests. Similar to the previous section our stress scenarios will consist of 3 cases; namely,

Table 8. Stress Test Results of Banks

| | Q32018 | Scenario 1 | Scenario 2 | Scenario 3 |
|---|---|---|---|---|
| B1 | 1.71% | 2.11% | 2.98% | 7.18% |
| B2 | 2.35% | 3.87% | 4.59% | 4.00% |
| B3 | 2.60% | 3.75% | 3.35% | 2.84% |
| B4 | 2.03% | 3.38% | 4.27% | 1.65% |
| B5 | 4.36% | 5.24% | 5.09% | 1.77% |
| B6 | 2.90% | 4.30% | 3.88% | 1.51% |
| B7 | 4.07% | 4.55% | 4.45% | 3.31% |
| B8 | 5.21% | 10.20% | 9.18% | 2.91% |
| B9 | 4.96% | 8.16% | 11.13% | 11.55% |
| B10 | 3.00% | 5.43% | 8.65% | 3.48% |
| Public | 2.62% | 4.11% | 4.10% | 3.41% |
| Private | 3.67% | 5.42% | 7.70% | 2.91% |
| Foreign | 3.75% | 7.32% | 7.86% | 5.71% |

baseline scenario, 2008 crisis scenario and 2001 crisis scenario. Due to the lack of data and complexity of calculation of capital adequacy ratio we have made several assumptions and used simplified estimations.

10 banks we have chosen account for the $84.50\%$ of total Turkish banking system by assets as of third quarter of 2018. Balance sheet data of each bank was obtained from data bank of the Banks Association of Turkey and it consists of quarterly data from the fourth quarter of 2004 to the third quarter of 2018. Stress test was conducted with projection for one year ahead, namely the fourth quarter of 2019 and the estimated results under each scenario are provided in the Table 8.

### 4.4 CAR calculation

Banks' main goal in conducting stress test is to estimate how resilient are their systems and how they will be affected in a case of stress scenario. This effect is estimated by the calculation of change in capital adequacy ratio (CAR), which should be maintained above the value determined by regulatory organizations and its stability is regarded as one of the indicators of resilience of banks. Failure to maintain the required levels of CAR may result in fines and even the cancellations of banking licenses.

In this section, we project the calculated NPL rate after stress test scenario to CAR of each bank. CAR is calculated as following:

$$CAR_t = \frac{Capital_t + Profit_t}{RWA_t}$$

where $CAR_t$ stands for capital adequacy ratio and is the fraction of Capital at time t plus Profit at time t divided by Risk-Weighted Assets at time t. In calculation of RWA we will use the RWA of banks calculated using the above formula and data provided by BRSA since we do not possess the information regarding the loan structure of banks. In our estimation in order to account for the changes in NPL rates for period $t + 1$ we will be using the equation given below:

$$CAR_{t+1} = \frac{Capital_t + Profit_t - CreditLoss_{t+1}}{RWA_t}$$

where apart from capital and profit at time t as in previous equation we have added Credit Loss at time $t + 1$. In calculation of Expected Credit Loss, we have followed the method used by Vukelic (2011) and Vukic (2014), which they calculated as following:

$$CL_{t+1} = PD_{t+1} \times EAD_t \times LGD_t$$

where $PD_{t+1}$ stands for probability of default of a loan, calculation of which might vary depending on whole spectrum of criteria such as credit type, borrowers balance sheet data and past credit activities and for simplicity we will assume $PD_{t+1}$ to be equal to NPL rates at time t+1. $EAD_t$ is the exposure at default which is the total

Table 9. Predicted Capital Adequacy Ratios of Banks

| | 2018Q3 | Scenario 1 | Scenario 2 | Scenario 3 |
|---|---|---|---|---|
| B1 | 16.22% | 14.98% | 14.47% | 12.00% |
| B2 | 17.42% | 15.38% | 15.00% | 15.31% |
| B3 | 18.28% | 16.50% | 16.69% | 16.93% |
| B4 | 18.48% | 17.04% | 16.66% | 17.78% |
| B5 | 17.38% | 14.79% | 14.86% | 16.50% |
| B6 | 14.86% | 11.96% | 12.24% | 13.84% |
| B7 | 17.23% | 13.91% | 13.98% | 14.81% |
| B8 | 16.01% | 10.36% | 10.93% | 14.40% |
| B9 | 21.02% | 16.26% | 14.53% | 14.28% |
| B10 | 16.58% | 13.59% | 11.82% | 14.66% |

amount of credit risk bank faces in case a borrower defaults and on the total bank's level it can be calculated as the difference between total loans and total NPL. $LGD_t$ is the loss given default and following the study of Küçükkocaoğlu and Altıntaş (2016), we will assume LGD to be equal to $50\%$. The ideal way of calculation of all of these ratios and indicators is the detailed classification of loans along with credit types and collateral information of the borrowers but due to unavailability of data and complexity of calculations we have used above specified assumptions. The results of the calculation of CAR for each bank in 3 scenarios is provided in the Table 9. According to the results in baseline scenario only bank 6 and bank 8 falls below the regulated CAR of 12% and in 2008 crisis scenario only bank 10 falls below the required CAR. Even though not many banks fall below the required CAR the drop in CAR is big and the required level is preserved thanks to current high levels of capitals in the banks. Smaller banks seem to be affected the most compared to larger banks.

# CHAPTER 5

# ARDL MODEL RESULTS

In this section we will be providing the results of our estimation using ARDL model. As mentioned previously our data covers periods between fourth quarter of 2002 to third quarter of 2018. We will be separately assessing the NPL rates of total banking sector and 15 separate credit sectors, then we look at 18 banks' individual NPL rates performances using the same model. In the previous chapter we have provided the results of our estimation using difference GMM model, in this chapter our aim is to assess how the estimation results will change across different methods, draw conclusions about robustness of our model. One main difference between difference GMM model and ARDL model is that the former is used to estimate panel data while the latter is used for the time series data but both of the models eliminates the estimation bias that could results from the correlation of dependent and independent variables. In the first part of the chapter we regress the dependent variable using the same lag structure. Including constant term in ARDL model and using same lag structure we receive pretty similar results to GMM model which does not have constant term. In credits to mortgage, construction, credit cards and others results are exactly the same. However, ARDL model with no constant term yielded different results. The results of the regressions are provided in Tables 10 and 11.

Table 10. Outcomes of ARDL Regressions with Constant Term

| | Tourism | Electr. Gas | Renting Real Est. | Mortg. | Vehicles | Fin. Interm. | Manuf. |
|---|---|---|---|---|---|---|---|
| $logit(NPL_{t-1})$ | 0.785 (0.000) | 0.879 (0.000) | 0.846 (0.000) | 0.903 (0.000) | 0.855 (0.000) | 0.597 (0.000) | 0.853 (0.000) |
| $g_t$ | −0.022 (0.046) | 0.018 (0.624) | −0.010 (0.591) | −0.019 (0.032) | −0.016 (0.001) | −0.024 (0.466) | 0.007 (0.156) |
| $g_{t-1}$ | −0.028 (0.040) | −0.086 (0.053) | −0.034 (0.130) | −0.017 (0.095) | −0.020 (0.001) | −0.028 (0.470) | −0.012 (0.046) |
| $g_{t-2}$ | −0.005 (0.759) | −0.006 (0.908) | −0.007 (0.803) | −0.026 (0.054) | −0.021 (0.008) | −0.032 (0.520) | −0.011 (0.159) |
| $g_{t-3}$ | 0.009 (0.640) | −0.051 (0.396) | −0.017 (0.597) | −0.017 (0.238) | −0.026 (0.002) | −0.066 (0.227) | −0.005 (0.494) |
| $g_{t-4}$ | 0.001 (0.943) | −0.081 (0.111) | −0.035 (0.195) | −0.001 (0.911) | −0.006 (0.381) | 0.007 (0.879) | −0.001 (0.989) |
| $u_t$ | −0.001 (0.974) | −0.082 (0.501) | −0.028 (0.659) | 0.013 (0.638) | 0.001 (0.939) | −0.032 (0.771) | 0.012 (0.445) |
| $u_{t-1}$ | 0.025 (0.326) | 0.018 (0.824) | 0.040 (0.355) | −0.005 (0.804) | 0.013 (0.224) | −0.034 (0.656) | 0.018 (0.126) |
| $u_{t-2}$ | −0.018 (0.461) | −0.071 (0.373) | −0.028 (0.506) | −0.010 (0.594) | −0.004 (0.726) | 0.047 (0.517) | 0.007 (0.530) |
| $u_{t-3}$ | 0.003 (0.883) | 0.002 (0.982) | −0.040 (0.304) | 0.006 (0.707) | 0.013 (0.170) | 0.013 (0.847) | −0.024 (0.018) |
| $u_{t-4}$ | 0.021 (0.423) | 0.056 (0.521) | 0.062 (0.176) | 0.017 (0.417) | 0.005 (0.713) | 0.039 (0.613) | 0.003 (0.787) |
| $fx_t$ | 0.485 (0.096) | 4.039 (0.000) | −1.087 (0.030) | −0.563 (0.010) | −0.419 (0.001) | 0.558 (0.498) | −0.651 (0.000) |
| $fx_{t-1}$ | −0.099 (0.622) | −0.186 (0.700) | −0.216 (0.431) | 0.188 (0.103) | 0.034 (0.609) | −0.695 (0.150) | −0.211 (0.009) |
| $fx_{t-2}$ | −0.033 (0.866) | 0.139 (0.774) | −0.161 (0.564) | 0.292 (0.014) | 0.026 (0.687) | −0.434 (0.367) | −0.041 (0.606) |
| $fx_{t-3}$ | −0.031 (0.865) | −0.584 (0.267) | −0.339 (0.250) | 0.164 (0.182) | 0.187 (0.008) | −0.463 (0.352) | −0.160 (0.047) |
| $fx_{t-4}$ | −0.141 (0.442) | −0.127 (0.816) | −0.131 (0.670) | 0.251 (0.054) | −0.324 (0.000) | −0.422 (0.404) | 0.070 (0.383) |
| $Cons$ | −1.070 (0.135) | 0.333 (0.790) | −0.496 (0.408) | −0.616 (0.042) | −0.636 (0.001) | −2.384 (0.060) | −0.614 (0.026) |

Table 11. Outcomes of ARDL Regressions with Constant Term

| | Constr. | Credit Cards | Metal. | Retail Trade | Agric. | Transp. | Textile | Other |
|---|---|---|---|---|---|---|---|---|
| $logit(NPL_{t-1})$ | $0.886$ (0.000) | $0.859$ (0.000) | $0.960$ (0.000) | $0.380$ (0.007) | $0.835$ (0.000) | $0.694$ (0.000) | $0.955$ (0.000) | $0.854$ (0.000) |
| $g_t$ | $0.007$ (0.347) | $-0.011$ (0.148) | $0.006$ (0.607) | $0.023$ (0.046) | $-0.001$ (0.863) | $-0.001$ (0.989) | $0.005$ (0.423) | $0.022$ (0.066) |
| $g_{t-1}$ | $-0.009$ (0.306) | $-0.005$ (0.338) | $-0.020$ (0.136) | $-0.002$ (0.857) | $-0.014$ (0.119) | $0.008$ (0.555) | $-0.015$ (0.026) | $0.010$ (0.480) |
| $g_{t-2}$ | $-0.013$ (0.251) | $-0.002$ (0.784) | $-0.005$ (0.796) | $-0.018$ (0.139) | $-0.005$ (0.680) | $-0.002$ (0.932) | $0.001$ (0.882) | $0.042$ (0.025) |
| $g_{t-3}$ | $-0.001$ (0.911) | $0.002$ (0.749) | $-0.009$ (0.624) | $0.008$ (0.521) | $-0.017$ (0.184) | $0.025$ (0.211) | $0.001$ (0.903) | $0.034$ (0.083) |
| $g_{t-4}$ | $-0.004$ (0.704) | $0.003$ (0.558) | $0.003$ (0.865) | $0.029$ (0.009) | $-0.003$ (0.763) | $0.010$ (0.550) | $0.015$ (0.050) | $-0.004$ (0.794) |
| $u_t$ | $0.006$ (0.806) | $0.021$ (0.129) | $0.052$ (0.165) | $0.107$ (0.000) | $0.003$ (0.918) | $0.051$ (0.201) | $0.031$ (0.095) | $0.147$ (0.001) |
| $u_{t-1}$ | $0.003$ (0.836) | $0.031$ (0.003) | $0.026$ (0.306) | $0.038$ (0.085) | $-0.006$ (0.725) | $0.046$ (0.102) | $0.013$ (0.311) | $0.032$ (0.239) |
| $u_{t-2}$ | $0.007$ (0.688) | $-0.003$ (0.781) | $-0.046$ (0.067) | $0.021$ (0.254) | $0.008$ (0.622) | $0.004$ (0.891) | $0.014$ (0.269) | $-0.034$ (0.206) |
| $u_{t-3}$ | $-0.016$ (0.278) | $0.005$ (0.580) | $-0.009$ (0.673) | $0.028$ (0.083) | $0.014$ (0.358) | $-0.036$ (0.143) | $-0.020$ (0.068) | $-0.018$ (0.456) |
| $u_{t-4}$ | $0.001$ (0.960) | $-0.026$ (0.021) | $0.002$ (0.946) | $-0.035$ (0.073) | $0.006$ (0.765) | $-0.011$ (0.689) | $-0.016$ (0.231) | $-0.069$ (0.020) |
| $fx_t$ | $0.037$ (0.846) | $-0.135$ (0.246) | $-0.558$ (0.062) | $0.200$ (0.307) | $0.007$ (0.971) | $-0.286$ (0.342) | $-0.901$ (0.000) | $-1.163$ (0.000) |
| $fx_{t-1}$ | $-0.129$ (0.213) | $-0.114$ (0.069) | $-0.004$ (0.978) | $-0.557$ (0.000) | $-0.078$ (0.449) | $-0.513$ (0.005) | $-0.276$ (0.001) | $0.150$ (0.347) |
| $fx_{t-2}$ | $-0.088$ (0.406) | $-0.119$ (0.047) | $-0.033$ (0.831) | $-0.247$ (0.081) | $0.028$ (0.789) | $-0.328$ (0.089) | $-0.114$ (0.150) | $-0.031$ (0.846) |
| $fx_{t-3}$ | $-0.126$ (0.259) | $-0.018$ (0.774) | $0.047$ (0.765) | $-0.129$ (0.324) | $0.153$ (0.168) | $-0.307$ (0.128) | $-0.107$ (0.211) | $0.356$ (0.041) |
| $fx_{t-4}$ | $0.242$ (0.042) | $0.010$ (0.873) | $0.221$ (0.188) | $0.154$ (0.220) | $-0.043$ (0.709) | $0.196$ (0.353) | $0.071$ (0.408) | $0.390$ (0.033) |
| $Cons$ | $-0.358$ (0.345) | $-0.675$ (0.059) | $-0.379$ (0.430) | $-3.733$ (0.000) | $-0.777$ (0.053) | $-1.798$ (0.005) | $-0.350$ (0.067) | $-1.064$ (0.024) |

In Table 12 and in Table 13 we have provided regression results of the same ARDL model without constant term. The problem of not including constant term lead to increased significance of explanatory variables, especially of the lag of NPL, making the model depend hugely on this variable, where most of the coefficient of the term was greater than $0.9$ and in credit cards it was even equal to $1.004$. As seen in the table the result of excluding constant term has also led to decrease of significance in GDP growth rate and unemployment rate coefficients due to increase in their standard deviations, while for exchange rate it has led to increase in coefficients and significance.

Table 12. Outcomes of ARDL Regressions without Constant Term

| | Tourism | Electr. Gas | Renting Real Est. | Mortg. | Vehicles | Fin. Interm. | Manuf. |
|---|---|---|---|---|---|---|---|
| $logit(NPL_{t-1})$ | 0.979 (0.000) | 0.863 (0.000) | 0.872 (0.000) | 0.939 (0.000) | 0.923 (0.000) | 0.751 (0.000) | 0.944 (0.000) |
| $g_t$ | −0.022 (0.058) | 0.019 (0.588) | −0.011 (0.568) | −0.019 (0.034) | −0.016 (0.004) | −0.023 (0.495) | 0.008 (0.136) |
| $g_{t-1}$ | −0.028 (0.039) | −0.081 (0.042) | −0.039 (0.075) | −0.020 (0.055) | −0.021 (0.001) | −0.042 (0.275) | −0.014 (0.017) |
| $g_{t-2}$ | −0.009 (0.600) | −0.002 (0.963) | −0.018 (0.488) | −0.035 (0.011) | −0.024 (0.006) | −0.075 (0.112) | −0.017 (0.024) |
| $g_{t-3}$ | −0.003 (0.855) | −0.041 (0.381) | −0.031 (0.299) | −0.028 (0.050) | −0.032 (0.001) | −0.120 (0.015) | −0.014 (0.073) |
| $g_{t-4}$ | −0.005 (0.739) | −0.074 (0.092) | −0.046 (0.039) | −0.010 (0.392) | −0.010 (0.169) | −0.032 (0.437) | −0.007 (0.244) |
| $u_t$ | −0.011 (0.775) | −0.061 (0.511) | −0.054 (0.339) | 0.008 (0.782) | 0.008 (0.629) | −0.133 (0.178) | −0.002 (0.877) |
| $u_{t-1}$ | 0.011 (0.660) | 0.023 (0.756) | 0.027 (0.500) | −0.017 (0.375) | 0.003 (0.776) | −0.090 (0.211) | 0.006 (0.538) |
| $u_{t-2}$ | −0.028 (0.271) | −0.069 (0.380) | −0.034 (0.408) | −0.017 (0.390) | −0.011 (0.312) | 0.030 (0.690) | 0.001 (0.994) |
| $u_{t-3}$ | 0.002 (0.914) | 0.001 (0.986) | −0.038 (0.317) | 0.006 (0.735) | 0.009 (0.379) | 0.018 (0.790) | −0.026 (0.015) |
| $u_{t-4}$ | 0.024 (0.379) | 0.046 (0.554) | 0.073 (0.097) | 0.020 (0.352) | 0.001 (0.932) | 0.081 (0.297) | 0.010 (0.415) |
| $fx_t$ | 0.430 (0.141) | 4.035 (0.000) | −0.977 (0.042) | −0.501 (0.025) | −0.366 (0.006) | 0.892 (0.285) | −0.570 (0.000) |
| $fx_{t-1}$ | 0.079 (0.634) | −0.178 (0.709) | −0.186 (0.493) | 0.175 (0.143) | 0.034 (0.626) | −0.481 (0.317) | −0.132 (0.072) |
| $fx_{t-2}$ | 0.197 (0.246) | 0.149 (0.756) | −0.139 (0.616) | 0.263 (0.031) | 0.041 (0.555) | −0.263 (0.589) | −0.037 (0.612) |
| $fx_{t-3}$ | 0.122 (0.484) | −0.620 (0.219) | −0.342 (0.244) | 0.112 (0.369) | 0.120 (0.099) | −0.408 (0.425) | −0.104 (0.192) |
| $fx_{t-4}$ | −0.089 (0.626) | −0.066 (0.893) | −0.173 (0.567) | 0.150 (0.226) | −0.431 (0.000) | −0.565 (0.276) | 0.102 (0.222) |

If the lag structure is not specified ARDL model in STATA allows optimal calculation of lag structure using either Bayesian information criterion (here on BIC) or Akaike information criterion. As every credit segment has its own dynamics and specifications, optimally they will also have differing lags structure. In this part of our study we present the result of the estimation using ARDL model with constant term and with optimal lags structure based on BIC. Using time-series data of each credit type we found that optimal lag structure for ARDL model includes one period lag of each macroeconomic variable. The results we get are in line with the model with four lags with constant term included, but in turn we lose the lags that are statistically

Table 13. Outcomes of ARDL Regressions without Constant Term

| | Constr. | Credit Cards | Metal. | Retail Trade | Agric. | Transp. | Textile | Other |
|---|---|---|---|---|---|---|---|---|
| $logit(NPL_{t-1})$ | 0.956 (0.000) | 1.004 (0.000) | 0.996 (0.000) | 0.995 (0.000) | 0.963 (0.000) | 0.945 (0.000) | 0.980 (0.000) | 0.976 (0.000) |
| $g_t$ | 0.005 (0.487) | −0.002 (0.676) | 0.004 (0.248) | −0.009 (0.344) | −0.001 (0.852) | −0.006 (0.658) | 0.005 (0.366) | 0.019 (0.130) |
| $g_{t-1}$ | −0.013 (0.107) | −0.007 (0.188) | −0.025 (0.039) | 0.003 (0.768) | −0.016 (0.079) | −0.003 (0.820) | −0.017 (0.014) | 0.001 (0.937) |
| $g_{t-2}$ | −0.019 (0.068) | −0.004 (0.589) | −0.013 (0.340) | 0.006 (0.685) | −0.009 (0.470) | −0.026 (0.158) | −0.004 (0.595) | 0.027 (0.132) |
| $g_{t-3}$ | −0.007 (0.545) | −0.001 (0.927) | −0.018 (0.224) | −0.011 (0.459) | −0.024 (0.062) | 0.002 (0.935) | −0.007 (0.363) | 0.015 (0.418) |
| $g_{t-4}$ | −0.008 (0.391) | 0.001 (0.938) | 0.003 (0.806) | 0.022 (0.096) | −0.008 (0.451) | 0.012 (0.485) | 0.007 (0.255) | −0.019 (0.224) |
| $u_t$ | 0.005 (0.828) | 0.018 (0.210) | 0.036 (0.248) | 0.076 (0.017) | −0.005 (0.839) | 0.011 (0.793) | 0.016 (0.340) | 0.117 (0.005) |
| $u_{t-1}$ | −0.001 (0.976) | 0.026 (0.011) | 0.018 (0.427) | −0.028 (0.179) | −0.017 (0.330) | 0.019 (0.501) | 0.003 (0.785) | 0.011 (0.672) |
| $u_{t-2}$ | 0.004 (0.802) | −0.011 (0.244) | −0.050 (0.038) | −0.013 (0.532) | 0.004 (0.824) | −0.019 (0.517) | 0.009 (0.476) | −0.051 (0.067) |
| $u_{t-3}$ | −0.016 (0.274) | 0.001 (0.924) | −0.009 (0.688) | 0.013 (0.497) | 0.012 (0.440) | −0.040 (0.132) | −0.020 (0.080) | −0.022 (0.378) |
| $u_{t-4}$ | 0.008 (0.634) | −0.031 (0.007) | 0.001 (0.674) | −0.051 (0.033) | 0.001 (0.973) | 0.015 (0.620) | −0.011 (0.395) | −0.062 (0.045) |
| $fx_t$ | 0.089 (0.620) | −0.043 (0.689) | −0.599 (0.042) | −0.267 (0.270) | 0.100 (0.607) | −0.210 (0.520) | −0.798 (0.000) | −1.143 (0.001) |
| $fx_{t-1}$ | −0.109 (0.282) | −0.154 (0.013) | −0.021 (0.890) | −0.427 (0.002) | −0.078 (0.461) | −0.371 (0.046) | −0.262 (0.002) | 0.108 (0.520) |
| $fx_{t-2}$ | −0.066 (0.521) | −0.139 (0.024) | −0.014 (0.928) | −0.152 (0.267) | 0.039 (0.721) | −0.115 (0.547) | −0.097 (0.228) | −0.093 (0.580) |
| $fx_{t-3}$ | −0.112 (0.307) | −0.019 (0.768) | 0.047 (0.764) | 0.144 (0.318) | 0.145 (0.209) | −0.123 (0.552) | −0.096 (0.271) | 0.287 (0.108) |
| $fx_{t-4}$ | 0.246 (0.038) | 0.006 (0.928) | 0.205 (0.215) | 0.295 (0.054) | −0.104 (0.368) | 0.340 (0.133) | 0.050 (0.570) | 0.249 (0.162) |

significant in four lag model. Even though we have not used these models in our stress testing, it might give a better understanding of each segment and be used in future studies. The results of the regression are provided in Table 14 and in Table 15.

Table 14. Outcomes of ARDL Regressions with Optimal Lag Structure Using BIC

| | Tourism | Electr. Gas | Renting Real Est. | Mortg. | Vehicles | Fin. Interm. | Manuf. |
|---|---|---|---|---|---|---|---|
| $logit(NPL_{t-1})$ | 0.776 | 0.877 | 0.849 | 0.947 | 0.856 | 0.651 | 0.839 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| $g_t$ | −0.015 | 0.003 | −0.006 | −0.015 | −0.015 | −0.022 | 0.006 |
| | (0.072) | (0.926) | (0.568) | (0.066) | (0.006) | (0.387) | (0.184) |
| $g_{t-1}$ | −0.019 | −0.077 | −0.018 | −0.015 | −0.012 | −0.010 | −0.008 |
| | (0.241) | (0.012) | (0.245) | (0.077) | (0.038) | (0.717) | (0.075) |
| $u_t$ | −0.019 | −0.057 | −0.007 | 0.043 | 0.038 | 0.053 | −0.023 |
| | (0.241) | (0.289) | (0.808) | (0.006) | (0.000) | (0.275) | (0.005) |
| $u_{t-1}$ | 0.006 | 0.074 | 0.029 | −0.002 | 0.024 | −0.009 | 0.011 |
| | (0.709) | (0.155) | (0.286) | (0.876) | (0.023) | (0.843) | (0.164) |
| $fx_t$ | 0.631 | 3.313 | −1.264 | −0.416 | −0.452 | 0.086 | −0.639 |
| | (0.003) | (0.000) | (0.001) | (0.033) | (0.001) | (0.888) | (0.000) |
| $fx_{t-1}$ | −0.102 | −0.054 | −0.119 | 0.125 | 0.041 | −0.403 | −0.252 |
| | (0.477) | (0.898) | (0.610) | (0.294) | (0.623) | (0.318) | (0.000) |
| $Cons$ | −1.025 | −0.865 | −0.891 | 0.651 | −1.082 | −2.348 | 0.875 |
| | (0.008) | (0.235) | (0.008) | (0.007) | (0.000) | (0.002) | (0.000) |

Table 15. Outcomes of ARDL Regressions with Optimal Lag Structure Using BIC

| | Constr. | Credit Cards | Metal. | Retail Trade | Agric. | Transp. | Textile | Other |
|---|---|---|---|---|---|---|---|---|
| $logit(NPL_{t-1})$ | 0.873 | 0.762 | 0.917 | 0.615 | 0.847 | 0.776 | 0.960 | 0.756 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| $g_t$ | 0.006 | −0.001 | 0.009 | −0.013 | −0.002 | −0.003 | 0.001 | 0.006 |
| | (0.327) | (0.751) | (0.354) | (0.085) | (0.688) | (0.800) | (0.801) | (0.622) |
| $g_{t-1}$ | −0.011 | −0.008 | −0.016 | −0.003 | −0.010 | 0.004 | −0.015 | −0.019 |
| | (0.110) | (0.036) | (0.098) | (0.673) | (0.129) | (0.703) | (0.004) | (0.104) |
| $u_t$ | 0.014 | 0.014 | 0.043 | 0.061 | 0.015 | 0.036 | 0.021 | 0.046 |
| | (0.213) | (0.058) | (0.014) | (0.000) | (0.182) | (0.051) | (0.027) | (0.030) |
| $u_{t-1}$ | −0.002 | 0.032 | 0.007 | −0.016 | 0.014 | 0.006 | 0.001 | 0.028 |
| | (0.881) | (0.000) | (0.660) | (0.290) | (0.221) | (0.730) | (0.910) | (0.189) |
| $fx_t$ | 0.008 | −0.210 | −0.283 | −0.190 | −0.086 | −0.157 | −0.794 | −0.802 |
| | (0.960) | (0.036) | (0.220) | (0.272) | (0.559) | (0.504) | (0.000) | (0.003) |
| $fx_{t-1}$ | −0.193 | −0.125 | −0.056 | −0.511 | −0.035 | −0.544 | −0.322 | 0.047 |
| | (0.041) | (0.038) | (0.685) | (0.000) | (0.693) | (0.000) | (0.000) | (0.776) |
| $Cons$ | −0.588 | −1.106 | −0.847 | −2.014 | −0.807 | −1.322 | −0.322 | −1.338 |
| | (0.014) | (0.000) | (0.001) | (0.000) | (0.002) | (0.000) | (0.007) | (0.000) |

# CHAPTER 6

# CONCLUSION

In this thesis, we have aimed to understand how well the Turkish banking system is positioned in terms of credit risk and how it will respond to external shocks. In our study we have conducted stress test of the credit risk of banking sector in Turkey. In developing our model, we have referred to integrated approach model developed by Wilson in 1997, where unlike his model we have added the lag of dependent variable along with other independent variables. After deciding on the model, we have regressed it using six different methods, two of which were excluded automatically since they did not provide unbiased results. The other four methods were different variations of GMM model that let avoid the bias stemming from the lag of dependent variable and we have chosen difference GMM model with macroeconomic variables taken as predetermined. In order to understand what factors affect NPL rates we have regressed them on various macroeconomic variables with different lag structures and found that apart from their lag they are affected by GDP growth rate, unemployment rate, exchange rate and four time lag of all of these variables.

Then we use this regression method and the lag structure of total NPL rate regression to regress the NPL rates of 15 different credit types and 10 largest Turkish banks. By using the lag structure similar to the lag structure of total NPL rate regression we look at how NPL rates of different credit types and NPL rates of individual banks separately responds to our stress scenarios, where using regression results, we estimate individual banks' future NPL rates in three stress test scenarios.

In our analysis as a macro stress-test scenarios, we developed a baseline scenario and two adverse scenarios based on historical approach in order to test the resilience of the exposure of credit risk of banking sector. Adverse scenario is derived from historical data and based on the performance of the Turkish economy and banking system during the 2008 and 2001 crises, while the baseline scenario is based on the forecast of the Turkish economy by OECD for 2019. In the third quarter of 2008 NPL rate of banking system is $3.20\%$; in baseline scenario it reaches $5.42\%$, in 2008 crisis scenario it reaches $6.07\%$ and in 2001 crisis scenario it increases only to to $4.14\%$.

As the main goal for the banks is to calculate their own resilience, stress-testing is used to assess the effect of stress scenarios on their capital adequacy ratios. In order to understand how banks perform individually, we also assess their CAR using the results of stress tests. Calculation of future CAR has helped us understand how resilient the banks are individually and if there is a need for further interventions and if Central Bank should take precautions like increasing capital requirements to help the banks avoid probable default. In all scenarios Turkish banks and the system overall seems to be resilient to the shocks, where, even under the most adverse scenario case of 2008 crisis scenario shows that, NPL ratio increases just up to $6.07\%$. The application of 2008 crisis scenario, however, yields the similar results despite the decade that has already passed. In 2008 crisis the banking system of Turkey has shown resilience, but not much has changed since then, despite the argument by IMF about improved FSAP since the last global financial crisis.

My study contributes to the literature by applying macro stress testing to NPL rates by credit types in Turkey, which, as argued by Vazquez, Tabak, and Souto (2012) grants NPL rates to be more sensitive to changes in macroeconomic variables. Besides, in my study I use different panel data techniques and apply and compare different GMM models and choose the difference GMM model, with macroeconomic variables taken as endogenously determined, to eliminate the bias from using lag of dependent variable-a method that was not previously used in Wilson-type models applied for the analysis of NPL rates in Turkey. In my study I conduct capital adequacy ratio calculation for each bank separately and find that some of the banks fail to meet required levels. Previous studies on Turkey did not report bank level calculations of CAR and they also reported that banking sectors CAR does not fail in adverse scenario cases.

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# APPENDIX A

## DERIVATION OF SHORT AND LONG RUN EFFECTS

In order to calculate the effects of a change in an independent variable on $npl_t$ we have taken the derivative of our model with respect to each independent variable. Below we will show the derivation with respect to $g_t$. Due to i.i.d. other independent variables' derivations will yield analogous results.

FOC with respect to $g_t$ is

$$\frac{\partial ln(\frac{npl_t}{1-npl_t})}{\partial g_{ti}} = \frac{\frac{\partial \frac{npl_t}{1-npl_t}}{\partial g_{ti}}}{\frac{npl_t}{1-npl_t}} = \frac{\frac{\partial npl_t}{\partial g_{ti}}}{(1-npl_t)(npl_t)} = \beta_1 \frac{\frac{\partial npl_{t-1}}{\partial g_{ti}}}{(1-npl_{t-1})(npl_{t-1})} + \sum_{s=0}^{q} \beta_{t-s} \tag{A.1}$$

from the derivation we get

$$\frac{\partial npl_t}{\partial g_{ti}} = (1-npl_t)(npl_t)(\beta_1 \frac{\frac{\partial npl_{t-1}}{\partial g_{ti}}}{(1-npl_{t-1})(npl_{t-1})} + \sum_{s=0}^{q} \beta_{t-s}) \tag{A.2}$$

meaning short run effect of change in GDP growth equals

$$(1-npl_t)(npl_t) \sum_{s=0}^{q} \beta_{t-s} \tag{A.3}$$

and the long run effect can be calculated by continuing the derivation of lag of $npl_t$ on the right hand side up to infinity, which yields

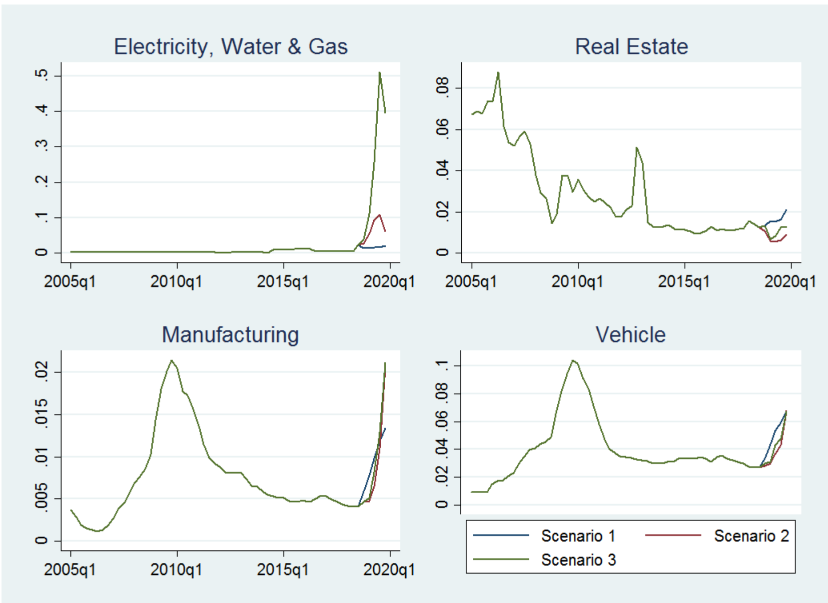
$$\frac{1}{1-\beta_1}(1-npl_t)(npl_t) \sum_{s=0}^{q} \beta_{t-s} \tag{A.4}$$

## APPENDIX B

## STRESS TEST RESULTS BY CREDIT TYPES

Apart from stress testing based on bank types we have also conducted stress test on credit types. We found that the credit types that are most exposed to risk in 2008 crisis scenario are mortgage, metallurgy, financial intermediary, vehicle and electricity, water and gas loans, where for mortgage loans in case of a shock NPL rates grew by $237.9\%$ and more than double for the other four credit types. In a baseline scenario, the most increase is expected in financial intermediaries, renting real estate service and mortgage loans. The biggest change occurred in the segments where the NPL rates were low and more than two times increase still stayed under plausible levels.

Figure "stress test results" below depicts the evolution of NPL rates in three scenarios for four largest credit segments. Table "stress test results by credit types" provides the detailed predicted future NPL rate outcomes for each credit type in all scenarios. The predictions were made for one year ahead, which is the fourth quarter of 2019.




Stress test results

Stress Test Results by Credit Types

| | Q32018 | Scenario 1 | Scenario 2 | Scenario 3 |
|---|---|---|---|---|
| Electricity, Gas and Water | 2.26% | 2.04% | 6.14% | 39.58% |
| Real Estate Renting Services | 1.24% | 2.09% | 0.89% | 1.27% |
| Mortgage | 0.41% | 1.34% | 2.08% | 2.12% |
| Vehicles | 2.73% | 6.74% | 6.82% | 6.75% |
| Financial Intermediaries | 0.38% | 0.65% | 0.36% | 0.44% |
| Manufacturing | 2.58% | 3.80% | 2.45% | 1.88% |
| Construction | 3.99% | 2.99% | 3.39% | 3.32% |
| Credit Cards | 5.42 % | 8.11% | 5.95% | 3.38% |
| Metallurgy | 2.65% | 4.98% | 4.27% | 2.04% |
| Turizm | 4.38% | 3.67% | 3.37% | 2.48% |
| Retail Trade | 3.81% | 5.03% | 5.30% | 1.53% |
| Agriculture | 2.89 % | 4.63% | 4.70% | 4.45% |
| Transportation | 1.76% | 1.84% | 1.04% | 0.42% |
| Textile | 2.39 % | 3.24% | 1.48% | 0.71% |
| Other | 6.37% | 10.76% | 8.08% | 0.94% |
| Total | 3.20% | 10.76% | 8.08% | 0.94% |