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Feedback effects of non-performing loans in EMU: A Panel VAR Approach

Master's thesis

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Declaration of Authorship

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Abstract

This thesis investigates long-run feedback effects between non-performing loans and their determinants in the Economic and Monetary Union countries using a panel VAR method with generalized impulse response functions and local projections. The results suggest a bi-directional relationship between the non-performing loans and their determinants. The non-performing loans ratio increases after a negative shock in GDP growth, rising unemployment, worsened fiscal balance and increasing risk. On the other hand, a positive shock to non-performing loans decreases the unemployment rate, risk and return on assets. Furthermore, we revealed a different magnitude of responses to shocks in core and periphery countries of EMU, which proves financial fragmentation.

JEL Classification	C23, C51, G21, E32, E44
Keywords	Non-performing loans, Panel VAR model, EMU, Generalised impulse response functions
Title	Feedback effects of non-performing loans in EMU: A Panel VAR Approach

Abstrakt

Tato diplomová práce zkoumá dlouhodobé efekty mezi nesplácenými půjčkami a jejich determinanty ve státech Evropské hospodářské a měnové unie pomocí panelové VAR metody, zobecněné funkce odezvy a metody local projections. Výsledky ukazují obousměrný vztah mezi nesplácených půjčkami a jejich determinanty. Podíl nesplácených půjček roste po negativním šoku v růstu HDP, rostoucí nezaměstnanosti a po zhoršení fiskální balance. Na druhou stranu, pozitivní šok na poměr nesplácených půjček sníží míru nezaměstnanosti, riziko a návratnost aktiv. Dále jsme odhalili, že velikost reakce se liší pro země na periferii a v jádru Evropské hospodářské unie, což prokazuje finanční fragmentaci.

Klasifikace JEL	C23, C51, G21, E32, E44
Klíčová slova	Nesplácené půjčky, Panelový VAR, Eurozóna, Zobecněná funkce odezvy
Název práce	Dopady nesplácených půjček na Eurozónu: Panel VAR analýza

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Acronyms

AIC Akaike Information Criterion

BIC Bayesian Information criterion

CADF Cross-section augmented Dickey-Fuller

CAR Capital adequacy ratio

CESEE Central and Eastern and South-Eastern Europe

CEE Central and Eastern Europe

EMU Economic and Monetary Union

EU European Union

FD First difference

FOD Forward orthogonal deviation

GDP Gross domestic product

GIRF Generalized impulse response functions

GMM Generalized method of moments

HQIC Hannan and Quinn Information Criterion

IRF Impulse response functions

IQR Interquartile range

LP Local projections

LTD Loan to deposit

MA Moving average

MMSC Moment and model selection criteria

NPL Non-performing loans

OECD Organization for Economic Cooperation and Development

OIRF Orthogonal impulse response functions

OLS Ordinary least squares

OMT Outright Monetary Transactions

ROA Return on assets

ROE Return on equity

SVAR Structural vector autoregression

VAR Vector autoregression

Master's Thesis Proposal

Author	Bc. Anna Bezuchová
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Proposed topic	Feedback effects of non-performing loans in EMU: A Panel VAR Approach

Motivation In the aftermath of the global financial crisis, the level of non-performing loans (NPL) started rising in the balance sheets of European banks. One of the most frequently used indicators to analyze how much banks are exposed to credit risk is the level of NPL. Therefore, the high level of NPL indicates that banks are exposed to high credit risk. Moreover, the high level of NPL delays recovery from a crisis (Aiyar et al., 2015). As the NPL and economy are related, it is crucial to know how NPL react to shocks of macroeconomic factors and vice versa - how NPL can affect the macroeconomy.

The NPL and the real economy affect each other. The impact of the real economy on NPL can be explained by the weakened ability of borrowers to pay their liabilities. On the other hand, the NPL can affect the real economy through the credit supply channel (Klein, 2013).

There are many studies analyzing NPL (Ari et al., 2019; Kjosevski et al., 2017; Nkusu, 2011; Rruga, 2020; Us,2020). Most of those studies focus mainly on determinants of NPL which fall into two categories: macroeconomic determinants and bank-specific determinants. Anastasiou et al. (2016a) identified the main determinants of NPL in the euro area using the generalized method of moments (GMM) approach. They identified economic growth and unemployment as important macroeconomic determinants of NPL. Klein (2013) analyzed NPL in Central, Eastern and South-Eastern Europe using the GMM approach and panel vector autoregression (VAR) approach. The author found that both bank-specific determinants and macroeconomic determinants significantly affect NPL. In addition to exploring determinants of NPL, the author examined the feedback effects of NPL. Anastasiou et al. (2016b) examined the causes of NPL in the euro area using fully modified ordinary least squares (OLS) and panel cointegrated VAR. They showed that countries on the periphery have different responses than core countries.

In my thesis, I will study mainly macroeconomic determinants of NPL in the Economic and Monetary Union (EMU) states. I will focus on the feedback effect between NPL and their macroeconomic determinants. Moreover, I will distinguish between core and periphery countries similarly to Anastasiou et al. (2016b). Many methods for analyzing NPL can be used (fixed effects, GMM, fully modified OLS). Nevertheless, I will employ a panel VAR approach that allows the analysis of feedback effects.

Hypotheses

Hypothesis #1: NPL are significantly influenced by shocks in their determinants.

Hypothesis #2: Determinants of NPL react on NPL shock.

Hypothesis #3: Periphery and core countries have different responses to shocks.

Methodology In order to test the hypotheses mentioned above, I plan to use the panel VAR analysis. Such method allows to examine the linkage between NPL and the real economy. Klein (2013) employed the panel VAR for evaluating the feedback effects between NPL and their determinants. Other econometric approaches will be used based on the literature review (e.g. Cholesky decomposition,...). Moreover, I will employ impulse responses functions (IRF) that shows the reaction of an endogenous variables to a shock over a time. Similarly to Anastasiou et al. (2016b), I will use several variables that were identified as macroeconomic determinants of NPL, e.g. GDP growth, unemployment, inflation. Moreover, some bank-specific variables will be also included, for example, return on equity, return on assets.

Expected Contribution The aim of this thesis is to explore more deeply the feedback effects of NPL on the real economy in EMU. Even though many studies analyzing the NPL have been done, those studies are mainly focusing on exploring determinants of NPL. In my thesis, I will primarily concentrate on the feedback effects between NPL and their determinants. Correspondingly to Anastasiou et al. (2016b), I will distinguish between core and periphery countries of EMU. Thus, the indication of financial fragmentation in the euro area could be revealed.

Outline

1. Introduction

2. Literature review
3. Data Description
4. Methodology
5. Empirical results
6. Conclusion

Core bibliography

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Chapter 1

Introduction

Following the global financial crisis, many European banks have been suffering from the increased level of non-performing loans (NPL) on their balance sheets. The high level of NPL in the bank balance sheet signalises that bank is exposed to credit risk. Moreover, the elevated level of NPL affects bank lending ability negatively. The high level of NPL is not the only problem for banks, but it is an issue for the whole economy. The NPL may affect the economic development of the country (Kosicova and Pastyrikova, 2020).

The level of NPL has significantly increased since the beginning of the global financial crisis in Europe (Makri et al., 2014). Moreover, the global financial crisis has caused financial fragmentation in the euro area. Anastasiou et al. (2016b) point out that the average level of NPL in the euro area was 12% in 2016. However, the level of NPL was below 2% in Germany and higher than 35% in Greece. They also found evidence that periphery countries are more vulnerable in the case of banking determinants of NPL. Therefore, it is also important to detect whether periphery countries respond differently to NPL shocks and shocks to their determinants.

Many studies have already been trying to uncover determinants of NPL (Anastasiou et al., 2016b; Klein, 2013; Ari et al., 2016; Kjosevski and Petkovski, 2016; Nkusu, 2011). Nevertheless, it is also essential to understand the connection between NPL and their determinants. Therefore, it is crucial to determine how NPL reacts to shocks to their macroeconomic and bank-specific determinants and vice versa. Understanding the dynamic nature can help the improvement of credit policies and government policies. The existing literature usually estimates either the determinants (Makri et al., 2014; Kjosevski and Petkovski, 2017) of NPL or the impact of NPL on macro variables. Only a few papers (e.g. Anastasiou et al., 2016b) estimate both directions within a framework of a panel VAR model. However, they focus mainly on short-term dynamics, and their sample ends already in 2013.

This study aims to reveal the reaction of NPL to shocks to their determinants and vice versa. Both groups of determinants will be analysed - the macroeconomic and the bank-specific determinants. Moreover, we will try to reveal the evidence of financial fragmentation in the euro area. More precisely, the reaction of core and periphery countries will be compared to detect whether those two groups of countries react similarly to NPL shocks. For this, the panel vector autoregression (VAR) approach will be used. The panel VAR approach allows analysing the feedback effect using the impulse response functions. The analysed dataset consists of bank-specific and macroeconomic data for 17 out of 19 countries from the Economic and Monetary Union over a period from 2004 to 2020.

Our results suggest that the connection between NPL and their determinants exists. More precisely, there is a bi-directional relationship between non-performing loans and their determinants. We detected a negative response of the NPL ratio to a positive shock to GDP growth, the government deficit, the current account balance, and ROA. On the contrary, the NPL ratio increases after an increase in the unemployment rate, risk aversion, and the loan to deposit ratio. Furthermore, the NPL ratio positively affects GDP growth. However, GDP growth tends to decrease after some time after shock. Furthermore, the current account balance increases after a positive NPL shock as well as the government deficit. Moreover, we found evidence of financial fragmentation in the euro area. Our results suggest that core and periphery countries react differently to NPL shocks and shocks to their determinants. In particular, we found that the trajectory of responses to shock is similar in most cases. However, the size of the effect differs.

The remainder of this thesis is organized as follows. Chapter 2 presents the problem of NPL and their determinants. This chapter also provides an overview of the existing literature on feedback effects between NPL and their determinants. Additionally, the problem of financial fragmentation and its development in the EMU countries is discussed. Chapter 3 provides the methodology which was used for the econometric model. The next chapter presents data that was used for the analysis. Chapter 5 includes the results of performed tests needed for analysis and evaluated results that were obtained. The last Chapter 6 summarizes the main results and ideas.

Chapter 2

Literature Review

2.1 Non-performing Loans

The definition of NPL can vary across countries as there is not any formal definition. The European Central Bank defines NPL as bank loans for which more than 90 days passed without any payment from the borrower (ECB). On the contrary, the Central Bank in Estonia defines the NPL as loans that are more than 60 days overdue (Bykova et al., 2019).

The important measure, the NPL ratio, which is the ratio of NPL to total loans, is used as a quality indicator of the credit portfolio of a bank (Jolevski, 2017). This ratio is also very commonly used as an indicator of aggregate credit risk (Macháček et al., 2018).

The rapid increase of the non-performing ratio can signalize the distortion of financial stability. Besides, the high level of NPL influences negatively the effect of bank lending on the real economy. Furthermore, the persistently high level of NPL slows economic activity. Banks with a high level of NPL cannot increase lending as part of their capital cannot be used due to the high level of NPL (Aiyar et al., 2015). The high level of NPL reduces bank profitability and increases its cost. Moreover, banks can require high provisions due to the high level of NPL. Therefore, it is crucial to reduce the level of NPL to increase credit growth. Moreover, Aiyar et al. (2015) suggest that the resolution of NPL would stimulate demand for new loans.

The NPL are an essential factor in the financial crisis. The growth of non-performing can signalize the onset of a banking crisis (Reinhart and Rogorr, 2011). Likewise, Bar et al. (1994) state that the high value of NPLs indicates the impending banking crisis. NPL are also more volatile during a crisis, and their high value can delay output recovery after a crisis (Ari et al., 2020).

2.1.1 NPL and banking crisis

The global financial crisis disturbed the relative stability of credit quality. One of the indicators of credit quality is the level of non-performing loans. Since the beginning of the financial crisis in 2008, the level of NPL has increased rapidly. Moreover, the high level of NPL in the balance sheet of banks delays recovery from crises (Aiyar et al., 2015). During the crisis, the level of NPL changes as the crisis evolves. Ari et al. (2020) claim that the evolution of NPL level during the crisis is inverse U-shaped or, in some cases, M-shaped. Therefore, for the U-shaped trajectory of NPL, they start rising rapidly at the onset of the crisis, peak after some years, and then start declining. Sometimes, the level of NPL declines and then starts rising again. Thus, the trajectory follows M-shape.

Some determinants can influence the development of the level of NPL during a crisis. The likelihood of an elevated level of NPL during the crisis is lower in countries with high GDP per capita and lower corporate debt. Moreover, the peaked level of NPL is lower in countries where banks are more profitable. Therefore, those banks have a higher return on assets. Furthermore, countries with lower pre-crisis government debt and lower pre-crisis credit growth have a high chance of resolving the high level of NPL sooner. Also, countries with high GDP growth have a higher chance of resolving an elevated level of NPL after the crisis. On the other hand, better pre-crisis corporate liquidity in the country can lower the probability of NPL resolution (Ari et al., 2020).

Ari et al. (2020) claim that most banking crisis suffers from an elevated level of non-performing loans. Anastasiou et al. (2016b) point out that the Asian crisis of 1997 was also caused by the high level of non-performing loans. During the Asian crisis, the level of NPL proliferated. Moreover, the NPL resolution was slow. The resolution of a high level of NPL lasted more than 7 years (Ari et al. 2020). On the other hand, the resolution of NPL during the Nordic banking crisis in 1990 was fast and effective. The level of NPL peaked at around 10 percent, and the non-performing loans were resolved within 3 years.

The level of non-performing loans in the Central and Eastern and South-Eastern Europe (CESEE) increased rapidly from an average value of 3 percent to 11 percent in the period starting from 2008 to 2011 (Klein, 2011). The high level of NPL became an issue in European Union. Furthermore, banks became more risk averse and cautious when they granted new loans (Bykova et al., 2019). Moreover, seven years after the beginning of the financial crisis in 2008, the level of the impaired asset was still high in Europe. In 2016, the non-performing loans in the euro area achieved an average level of 12 percent. However, the level of non-performing loans in Germany was only 2 percent. On the other hand, the level of non-performing loans exceeded 35 percent in Greece. Anastasiou et al. (2016b) highlight the difference between periphery and core countries of the euro area. Moreover, periphery banks face non-performing loans as the most significant challenge.

The resolution of the high amount of NPL in Europe is an important topic not only for policymakers. Aiyar et al. (2017) describe three pillars proposed by IMF analysis needed to decrease the impairment loans in the balance sheet of banks. Firstly, oversight over banks should be more intense, and banks should be motivated to restructure impaired loans. Secondly, there should be reforms to improve the insolvency framework and debt enforcement regimes. Thirdly, the market structure should be improved to develop distressed debt markets.

2.1.2 Determinants of NPL

The level of non-performing loans can be influenced by its determinants directly or indirectly (Kocisova and Pastyriková, 2020). Moreover, examining and exploring those indicators of NPL is essential. After the crisis, policymakers try to monitor NPL and then implement policy tools to decrease the level of NPL. Therefore, it is crucial to understand what drives the NPL and how to possibly decrease the level of impaired loans.

The existing studies categorize factors influencing NPL into two groups. The first group of NPL determinants consists of macroeconomic conditions that affect the creditworthiness of borrowers. The common variables classified among macroeconomic determinants are, for example, gross domestic product (GDP), unemployment, inflation, policy rates, and exchange rate. The second group of NPL factors includes bank-specific variables which influence NPL. Bank-specific factors influencing NPL are, for instance, return on equity (ROE), return on asset (ROA), credit growth, excessive lending, and capital adequacy ratio (CAR).

Plenty of research investigates both groups of determinants - macroeconomic and bank-specific. Makri et al. (2014) inspect determinants of NPL in Eurozone for the period 2000-2008 using the difference Generalized Method of Moments (GMM) estimation. Additionally, Kjosevski and Petkovski (2017) examine factors influencing NPL in Baltic states using data from the period 2005-2014. He implements the difference GMM estimation like Makri et al. (2014).

Despite the importance of both groups of factors, some papers study only one group of NPL determinants. More specifically, Rachman et al. (2018) examine bank-specific determinants of NPL in Indonesia. They used data from the period 2008-2015 and estimated fixed effect regression in their study. On the contrary, Touny and Shehab (2015) analyze the second group of factors influencing NPL, macroeconomic factors, in some Arab countries. For their analysis, the GMM estimation was used. Similarly, Szarowska (2015) focused only on macroeconomic determinants influencing NPL in the Central and Eastern European countries. She performed a fixed effect analysis on panel data from the period 1999-2015. Likewise, Škarica (2014) analyzed the macroeconomic drivers of NPL in selected European emerging markets. He performed fixed effect estimation for panel data starting in the third quarter of 2007 to the third quarter of 2012.

2.1.3 Macroeconomic determinants

The macroeconomic determinants are external conditions linked to the capacity of a borrower to repay debt (Klein, 2013). Those factors are found to have a significant effect on the level of NPL (Anastasiou et al., 2016b; Szarowska, 2015; Klein, 2013).

One of the most important macroeconomic factors influencing NPL is **Gross Domestic Product (GDP)**. The NPL are found to have countercyclical behaviour. Thus, when positive economic indicators (e.g. employment) grow during the expansion, a low level of NPL can be observed. On the other hand, the level of NPL is higher during a recession. Those observations can be explained by the ability of a borrower to repay a loan. During the expansion, borrowers are better off, and their ability to repay debt is higher. Therefore, the level of NPL is low. On the other hand, during the recession, positive economic indicators are falling, and the level of NPL rises due to the lowered capability of the borrower to repay a loan. Klein (2013) found a significant negative relationship between NPL and lagged real GDP growth in the euro area. Likewise, Roman and Bilan (2015) examined that the real GDP growth rate has a major negative impact on NPL in European Union (EU) countries. Anastasiou et al. (2016b) also found a significant negative impact of the GDP growth rate on the NPL level in the euro area. Further, they investigated the effect of the output gap as a possible determinant of NPL. The output gap is the difference between actual GDP and potential GDP. Their result suggests that the output gap has a negative impact on the level of NPL in the euro area.

Unemployment serves as another important driver of NPL. The correlation between unemployment with NPL is often determined to be positive. Hence, with higher unemployment, borrowers may have difficulty to repay loans. Thus, the level of NPL is more likely to be higher. Anastasiou et al. (2016b) claim that high unemployment may cause the discouraged worker effect. The discouraged worker effect causes that worker decides to leave the labour market due to bad conditions in the market. Thus, the worker believes that there is no suitable job available. Furthermore, higher unemployment causes also lowered consumption which can lead to lower profits for businesses. Thus, their ability to repay loans can also be negatively affected due to their lower profits. Klein (2013), and Roman and Bilan (2015) found a positive correlation between NPL and unemployment. Moreover, Szarowska (2015) indicated unemployment as the most crucial macroeconomic determinant in the Central and Eastern European countries as an increase of 1 percentage point leads to an increase of NPL by 0.58 percentage points, according to her results. Likewise, Makri et al. (2014) and Kjosevski and Petkovski (2017) examined the positive relationship between unemployment and NPL.

Inflation stands out as a crucial determinant influencing the level of NPL. Unlike the determinants mentioned above, the effect of inflation is ambiguous. Therefore, the relationship between inflation and NPL can be positive or negative. Inflation causes a fall in purchasing power. Thus, higher inflation may reduce the real value of a loan, and it can be easier to repay the loan for the borrower. On the other hand, higher inflation reduces the real income of borrowers as wages are sticky, and the borrower can have difficulties to repay a loan. Thus, the level of NPL will rise. Kjosevski and Petkovski (2017) examined the positive relationship between inflation and NPL in Baltic states. On the contrary, Szarowska (2015) found a negative relationship between inflation and NPL in the CEE countries. Likewise, Touny and Shehab (2015) indicate that inflation rate and NPL have an adverse relationship using data for some Arab countries.

Another macroeconomic determinant that was found to affect NPL is the

exchange rate. The exchange rate can have a positive or a negative relationship with NPL. The positive relationship between exchange rate depreciation and NPL can be reported in countries with flexible exchange rate regimes and large amounts of lending in foreign currency (Klein, 2013). On the contrary, exchange rate depreciation increases the volume of exports. Thus, the position of export-oriented firms is improved, and their ability to repay a loan is higher. Therefore, the NPL ratio can be reduced (Beaton et al., 2016; Beck et al., 2015). Kocisova and Pastyriková (2020), who examined determinants across European Union countries, found a negative relationship between NPL and nominal effective exchange rate. Thus, exchange rate appreciation reduces the level of NPL.

Risk aversion is the macroeconomic determinant that influences NPL. Higher global risk aversion increases NPL. Klein (2013) used VIX index as a proxy variable for risk aversion. He reports this variable as significant in his results. Thus, risk aversion serves as a macroeconomic determinant of NPL. Espinoza and Prasad (2010), who investigated NPL and their macroeconomic effects in the Gulf Cooperative Council countries, obtained the same result.

Policy rate belongs among important macroeconomic determinants of NPL. Interest rate and NPL should have a positive relationship. The increase in interest rate influences the ability to service debt. Interest rate increase worsens the ability to repay a debt of a borrower. In other words, it makes loan repayments more expensive, and the probability of default is higher (Ghosh, 2017). This effect is higher if the interest rate is floating. Espinoza and Prasad (2010) found that an increase in interest rate worsens the NPL ratio. Beck et al. (2015) examined that lending interest rate has a positive statistically significant impact on the level of NPL. Szarowska (2015) also obtained this positive relationship for CEE countries.

Public finance variables are macroeconomic determinants of NPL. Those variables can be, for example, public debt and government budget variables. Anastasiou et al. (2016b) examined whether government budget surplus/deficit serves as a macroeconomic determinant of NPL. A budget surplus can cause an increase in the NPL because of a restrictive fiscal position. On the contrary, a budget surplus can signal cheaper financing, and the level of NPL can fall. Roman and Bilan (2015) found a positive relationship between budget balance and NPL.

There are plenty others macroeconomic determinants of NPL which are, however, not widely used. As one of the possible macroeconomic determinants, the housing price index is expected to have a negative relationship with NPL. Ghosh (2017) obtained this negative relationship in his results. Beck et al. (2015) investigated whether share prices influence NPL. The share price indicator was used instead of the house price index, for which data are insufficient. They believe that share price and housing price are correlated. They found that an increase in share prices can negatively affect the level of NPL. This effect can be observed in countries where the stock market relative to GDP is essential. The share prices index was also used as a macroeconomic indicator by Škarica (2014.) However, he obtained an insignificant coefficient as the Central and Eastern European regions have a small market capitalization.

2.1.4 Bank-specific determinants

Four hypotheses

Berger and De Young (1997) suggest four hypotheses in their study related to the linkage between efficiency and NPL. They investigated the relationship between NPL and cost efficiency in their paper. Those four hypotheses are named "bad luck", "bad management", "skimping", and "moral hazard". All hypotheses are non-mutually exclusive. Hence, all of them can potentially affect banks at the same time.

Firstly, the "bad luck" hypothesis proposes that external events can cause an increase in NPL. Berger and De Young (1997) claim that banks have to spend expenses on loans that are past due. These additional costs are related, for example, to the additional monitoring of defaulted debtors, analyses and negotiation of workout arrangements, etc. Therefore, cost efficiency can decrease as a result of the elevated level of NPL.

The second hypothesis proposed by Berger and De Young (1997) is the "bad management" hypothesis related to management practices. They suggest that poor management practices can cause low cost efficiency. Cost efficiency can be affected directly due to operating expenses controlling, which are not sufficient. Poor managers can control expenses insufficiently because of their poor skills in credit scoring. Moreover, the skills of poor managers for appraising loans are also not sufficient. Therefore, the level of NPL rises due to weak management practices. Therefore, both hypotheses predict that NPL and cost efficiency are negatively linked.

The "skimping" hypothesis, the third hypothesis, suggests that monitoring of loans has an influence on cost efficiency and NPL. When maximizing profit, the bank has to choose whether it is affordable to decrease operating costs by skimping expenses on monitoring and underwriting loans in the short run for the price of a possible increased volume of NPL in the long run. Skimping resources intended for borrowers monitoring, customers loan screening can be seen as effective in the presence as operating expenses are decreasing, and the quantity of loans remains the same. However, the level of NPL will start rising in the future as there is lower attention to the loan portfolio. Thus, the "skimping" hypothesis suggests a positive relationship between cost efficiency and NPL compared to the first two hypotheses.

The fourth hypothesis is the "moral hazard" hypothesis which was also examined by Keeton and Morris (1987). This hypothesis is linked to excessive risk-taking by the bank. According to the moral hazard hypothesis, when less capitalized banks increase the riskiness of loan portfolios due to the moral hazard incentive of managers, the volume of NPL increases in the future. Moreover, Keeton and Morris (1987) suggest that high capitalized banks are unwilling to provide risky loans. Following this, the level of NPL decreases. Therefore, capital requirements and NPL are negatively associated.

Determinants

Capital adequacy stands out as a bank-specific determinant influencing NPL. Capital adequacy tends to have a negative relationship with NPL as a result of the moral hazard hypothesis proposed by Keeton and Morris (1987) and Berger and De Young (1997). Analyzing data for Spanish banks in the period 1985-1997, Salas and Saurina (2002) supported this hypothesis by exploring the negative relation between capital adequacy and NPL. Likewise, Abid et al. (2013) found evidence for moral hypothesis investigating Tunisian banks. The results of Klein (2013) also confirm the moral hazard hypothesis as his results suggest a significant negative link between the equity-to-asset ratio and the level of NPL.

Efficiency is an essential bank-specific determinant, and its relationship with NPL was defined in the bad luck hypothesis, bad management hypothesis, and skimping hypothesis. An efficient bank is doing its business activities with relatively low costs (Rachman et al., 2018). According to the bad luck hypothesis and bad management hypothesis, the cost efficiency should be negatively linked with NPL. Podpiera and Weil (2008) supported the bad management hypothesis in their analysis of Czech banks in the period 1994-2005. Likewise, Williams (2004) similarly found evidence for the bad management hypothesis using data from European saving banks. The positive linkage between the cost efficiency and NPL suggested by skimping hypothesis was revealed by Rossi et al. (2005), who examined data for Tunisian banks.

Profitability serves as another determinant from the banking sector influencing NPL. Profitability can be linked to the hypothesis stated by Berger and De Young (1997) because cost efficiency changes affect profitability (Rachman et al., 2018; Ghosh, 2017; Klein, 2013). Related to profitability, Louzis et al. (2012) suggested that profitability is negatively associated with NPL in their bad management II hypothesis. As an indicator of the profitability of the bank, the return on asset (ROA), which is the ratio of net income divided by total assets, is widely used (Ghosh, 2017). According to Godlewski (2004), Ahmed (2003), and Makri et al. (2014), return on equity (ROE) and net interest margin (NIM) can be used as indicators of profitability. Makri et al. (2014) determined a significant negative relationship between ROE and NPL. Likewise, Klein (2013) found an adverse relation between ROE which serves profitability indicator and NPL. Furthermore, Anastasiou et al. (2016b) also supported the bad management hypothesis with their results.

Credit growth belongs among crucial bank-specific determinants. Credit growth is negatively linked to loans quality. Thus, credit growth and the NPL ratio should be positively linked. Increased credit supply lowers loan interest rate (Keeton, 1999). Vithessonthi (2016) observed the positive link between credit growth and NPL in Japan. However, this relationship has transformed into a negative one after the onset of the global financial crisis of 2007. Alihodžić and Ekşi (2018) argued that NPL and credit growth rate are negatively correlated by analyzing data from Turkey and some Balkan countries from the period 2007-2017.

Among other bank-specific determinants belongs, for example, **excessive lending**. Klein (2013) used a loans-to-asset ratio as an indicator for this determinant. He found a positive relationship between the loans-to-asset ratio and NPL. Besides, Keeton and Morris (1987) claim that excessive lending can lead to a higher level of NPL. The positive link between excessive lending and NPL was also revealed by Salas and Suarina (2002).

A bank size can also influence the level of NPL (Anastasiou et al., 2016b; Us, 2020). Bigger banks can be risk lovers; thus, they can grant loans even to borrowers of lower quality (Stern and Feldman, 2004). Louzis et al. (2012)

formulated a diversification hypothesis suggesting that bank size and the share of non-interest income of total income are both negatively linked to NPL. Salas and Saurina (2002) found a negative link between bank size and NPL. They also demonstrated that size allows banks for more diversification opportunities. Rajan and Dhal (2003) also support this diversification hypothesis.

2.2 Relationship of NPL with the real economy

The relationship between NPL and the real economy has been investigated by many researchers (Klein, 2013; Kjosevski and Petkovski, 2017; Nkusu, 2011; Anastasiou et al., 2016b).

The impact of the real economy on the level of NPL can result from the weaker capacity of a borrower to repay a loan. On the other hand, NPL can affect the real economy through the credit supply channel (Klein, 2013). Additionaly, Mohd et al. (2010) claim that the high cost related to managing a high level of NPL and lower capital resulted from provisioning are another explanation of the influence between NPL and the real economy. As both those factors influence credit supply, they can also influence the real economy. Myers (1977) also suggests that the effect between the real economy and NPL can also be done through non-credit supply channels. Companies with a high amount of debt can be discouraged from investing in a new project because future profits will be shared with banks to service their debts.

Nkusu (2011) focused on advanced economies using annual data for 26 countries from the period 1998-2009. He investigated the feedback effect by performing a panel vector autoregressive model. The author investigated that adverse shocks to macroeconomic performance and credit to the private sector negatively influence the level of NPL. Moreover, a NPL shock causes deterioration in asset prices, economic growth and credit to the private sector. Moreover, the shock in NPL leads to a decline in house prices.

Klein (2013) analyzed feedback effects in Central, Eastern and South-Eastern Europe (CESEE). He investigated data from the period 1998-2011 using a panel VAR estimation. He found that a positive shock in the credit-to-GDP ratio and real GDP decreases the level of NPL. Furthermore, a positive shock to inflation leads to an increase in NPL in the subsequent year. Moreover, his result suggests the presence of a feedback effect from the banking sector to the real economy. More precisely, the NPL shock has a significant negative impact on the credit-to-GDP ratio, inflation and real GDP growth.

Us (2020) studied the feedback effects for the Turkish banking sector in the period 2002-2017 using a panel VAR approach. The author also focused on changes in responses to shocks in the period before and after a crisis. He found that NPL respond to shock in macroeconomic variables, such as, inflation, unemployment and GDP growth. He revealed that NPL react negatively to a positive shock in GDP growth. Moreover, a positive shock in inflation and unemployment causes a higher level of NPL. He also demonstrated that a positive shock to NPL affects inflation positively.

Kjosevski and Petkovski (2017) explored feedback effects from the banking sector on the real economy for Baltic countries. Similarly to Us (2020), they applied a panel VAR methodology to explore the feedback effects. They determined strong linkages between the real economy and the banking sector. The level of NPL responds to shock in GDP growth. Furthermore, the positive shock to NPL influences on the GDP growth, unemployment, and inflation.

Anastasiou et al. (2016b) studied the linkage between the banking system and the real economy of the euro area in the period 2003-2013. Using the Generalized Impulse Response Functions, they found that positive shocks in unemployment, personal income as a percentage of GDP, and interest rate margin increases the level of NPL. On the other hand, a positive shock in GDP growth, bank size and credit to the private non-financial sector ratio decreases NPL.

Beaton et al. (2016) focused on NPL in Eastern Caribbean Currency Union. He performed a panel VAR analysis using a dataset from 1996 to 2015. They found strong macro-financial linkage in their results. They explored that an increase in NPL negatively affects economic performance. Thus, real GDP growth and CPI inflation decrease. Results also suggest that macroeconomic determinants significantly affect asset quality (i.e. NPL). Higher GDP growth leads to a decrease in NPL.

Lee and Rosenkranz (2020) studied the feedback effects in Asia using a panel VAR framework. They perform an analysis of data for Asia from the period 1994-2014. Their results show that a positive shock in the NPL ratio negatively affects GDP growth, credit supply, and the policy rate. On the other hand, unemployment is positively affected by shock to NPL. Moreover, NPL is negatively affected by the positive shock to GDP growth and credit supply. Conversely, rising unemployment has a positive effect on the NPL level.

There are many other studies focusing on the linkage between the real economy and the banking sector. Love and Ariss (2013) investigated the linkage between the economy and the banking sector in Egypt. They used panel data from the period 1993-2010. They estimated their data using the panel VAR framework. Espinoza and Prasad (2010) examined data from 80 banks of the Gulf Cooperation Council region. Their results suggest that an increase in the NPL level negatively influences credit growth.

2.3 Financial fragmentation

Berenberg-Gossler and Enderlein (2016) characterize financial fragmentation as a disintegration process that can cause fundamental problems. They insist that if the access to credit is not the same for all agents in a monetary union, the central bank may not be so efficient in monetary policy. Moreover, the occurrence of cross-country heterogeneity is stronger after a crisis (Bijsterbosch and Falagiarda. 2015; Berenberg-Gossler and Enderlein, 2016)

The financial fragmentation in the euro area was investigated in many studies (Anastasiou et al., 2016b, Zaghini, 2016; Mayordomo et al., 2015). Zaghini (2016) focused on the corporate bond market. He explored that financial integration was achieved in the euro area before the crisis. However, financial fragmentation increased significantly during the sovereign debt crisis. Mayordomo et al. (2015) investigate financial fragmentation in the interbank market in Europe. They found that the financial fragmentation has substantially increased during the crisis and its level was considerably higher in the periphery than in core countries. Anastasiou et al. (2016b) explored fragmentation in determinants of non-performing loans in EMU countries. They found that the NPL level was significantly higher in the periphery in 2008. Al-Eyd and Berkmen (2013) examined the most important factors that influence fragmentation in the euro area. They investigate the fragmentation in the euro area in several different ways. They claim that the outflow of the capital from the periphery countries was much more significant than from core countries. Furthermore, the level of NPL increased significantly in the periphery. Moreover, the difference in bond spread became extensive in core and periphery countries after the crisis as opposed to the period before the crisis when the difference was negligible.

2.3.1 Development of financial fragmentation in the euro area

The integration of financial markets in the euro area has been a critical issue in the European Union (Mayordomo et al., 2015). Financial integration is important mainly due to optimal capital allocation. On the contrary, the persistence of financial fragmentation in the euro area could lead to capital allocation, which is not optimal (Blot et al., 2016). Horváth (2017) states that financial integration significantly increased after adopting the Euro as the currency in 1999.

The global financial crisis brought an increase in financial fragmentation in the euro area. In 2008 and 2009, there was an extensive decrease in international trade (De Sola Perea and Van Nieuwenhuyze, 2014). Horváth (2017) claims that the highest financial fragmentation was reached in the period from 2011 to 2012. De Sola Perea and Van Nieuwenhuyze (2014) state that the high level of financial fragmentation is dangerous for an effective monetary policy. Al-Eyd and Berkmen (2013) claim that the financial fragmentation decreased after the Outright Monetary Transactions (OMT) framework announcement by the European Central Bank in 2012. The OMT aimed to eliminate redenomination risk. The redenomination risk is the risk that the asset denominated in the euro currency will be redenominated into another currency after a possible break-up of the euro (Zaghini, 2016). After adopting the OMT framework, the spreads of government bonds in Italian and Spanish decreased to the level of 2010. Similarly, Horváth (2017) claims that government bonds yields declined significantly after the OMT announcement in Southern European countries. Moreover, he states that despite the improvement in the euro area market, the level of financial integration did not return above the level before the sovereign debt crisis.

Chapter 3

Methodology

Researchers use several econometric approaches when studying NPL. Studies that investigate determinants of NPL use, for example, a GMM estimation, a panel VAR approach, and a fully modified ordinary least squares (OLS). Anastasiou et al. (2016a) investigated determinants of NPL in the euro area using the GMM approach. Klein (2013) examined determinants of NPL using the panel VAR method. Moreover, he used the panel VAR approach and impulse response functions to explore the feedback effect between NPL and their determinants. Similarly, Anastasiou et al. (2016b) used the cointegrated panel VAR method in their study. They focused on the causes of NPL. Moreover, they also included the analysis of NPL using the fully modified OLS.

Feedback effects between NPL and their determinants are very often investigated using the panel VAR method (Us, 2020; Beaton et al., 2016; Lee and Rosenkranz, 2020; Nkusu, 2011; Kjosevski and Petkovski, 2017; Anastasiou et al., 2016b, Love and Ariss, 2014). Therefore, the panel VAR analysis can be considered as a suitable econometric method for the analysis. Not only a panel VAR method will be employed, but also impulse response functions (IRF) will be used so that the reaction of endogenous variables over time can be explored.

3.1 Vector Autoregressive Models

Vector autoregressive approach became very popular mainly after Sims (1980) introduced the VAR method as an alternative to multivariate simultaneous equations models (Brooks, 2019). Nowadays, VAR models are extensively used for multivariate analysis. Moreover, those models can also be used for forecasting (Lütkepohl, 2007).

Brooks (2019) states several advantages of vector autoregressive models. One of the numerous advantages of this econometric approach is that there is no distinction between endogenous and exogenous variables because all variables are treated as endogenous in VAR models. Another advantage is that variables can also depend on other variables than just on their lags or their combinations. Moreover, the forecast ability of VAR models is better than that in structural models. On the other hand, there are also a few disadvantages of VAR models. Among the downsides of the VAR model belongs, for instance, the determination of the number of lags. As there are several approaches to determining the appropriate lags, the results of those methods may vary. Another drawback of the VAR model is a large number of parameters in equations. More precisely, there are $k+kg^2$ parameters in each equation, where g is the number of variables and k is the number of lags for each variable.

The VAR models methodology is based on the methodology of the univariate autoregressive models as it is theirs extension. The basic structural form of the vector autoregressive model with two variables y_{1t} and y_{2t} (i.e. bivariate VAR) has the following form:

$$y_{1t} = \beta_{10} + \beta_{11}y_{1,t-1} + ... + \beta_{1k}y_{1,t-k} + \alpha_{11}y_{2t-1} + ... + \alpha_{1k}y_{2t-k} + u_{1t}$$

$$y_{2t} = \beta_{20} + \beta_{21}y_{2,t-1} + ... + \beta_{2k}y_{2,t-k} + \alpha_{21}y_{1t-1} + ... + \alpha_{2k}y_{1t-k} + u_{2t}$$

where u_{it} are white noise disturbance with zero mean ($E(u_{it}) = 0$ for i=1, 2) and disturbances are not autocorrelated ($E(u_{1t}u_{2t}) = 0$).

These two equations create a structural VAR (SVAR). Structural VAR reveals contemporaneous linkages between variables using economic theory (Stock and Watson, 2001). However, the OLS estimation cannot be used for SVAR because variables used in the regression are correlated with the error term; therefore, the endogeneity occurs, and Gauss-Markov assumptions are violated.

The structural VAR can be transformed by algebraic adjustment to a reduced form VAR which has the following form:

$$y_t = A_0 + A_1y_{t-1} + e_t.$$

In reduced form VAR, each variable is a function of its lag values. The structure enables us to estimate each equation by OLS regression. The error terms in reduced VAR indicate the unexpected movements after the past is taken into account (Stock and Watson, 2001).

3.2 Panel Vector Autoregressive Models

The panel VAR model is the extension of the VAR model introduced by Holtz-Eakin et al. (1988). A panel VAR approach serves as an appropriate econometric method to show how feedback effects between NPL and their determinants are strong and their duration.

Plenty of advantages of panel VAR models exist. Among those advantages are, for example, easy performance and a small set of restrictions (Canova and Ciccarelli, 2013). Moreover, not only static interdependencies can be captured by the panel VAR model, but also dynamic ones can be captured by those models. In panel VAR models, cross-sectional dynamic heterogeneities are also taken into account. (Canova and Ciccarelli, 2013)

A structure of a panel VAR model is very similar to the structure of the VAR model as all variables are treated as endogenous and interdependent (Canova nad Ciccarelli, 2013). However, the extra object in the structure is a cross-sectional dimension. Therefore, the structure of the panel VAR model is the following:

$$y_{it} = A_{0i}(t) + A_i(\ell)Y_{t-1} + u_{it} \qquad i = 1, ..., N \;\; t = 1, ..., T$$

where i serves as an index for cross-sectional dimension (i.e. country, region, market, sector etc.), $Y_t = (y'_{1t}, y'_{2t}, ..., y'_{Nt})'$, and u_{it} is a vector of random disturbances G×1. (Canova and Ciccarelli, 2013)

Canova and Ciccarelli (2013) mention 3 important features of panel VAR models:

- dynamic interdependencies,
- static interdependences,
- cross-sectional heterogeneity.

The first feature of panel VAR models, the dynamic interdependencies feature, states that the model for unit i includes lags of all variables. The second characteristic, static interdependences, characterizes the error term u_{it} as correlated across units i. Cross-sectional heterogeneity, the third feature, states that the coefficients of the slope, the intercept and the variance of the shocks can differ for each unit. However, it is not necessary to have all mentioned features at once.

Abrigo and Love (2016) suggest the estimation of parameters of panel VAR model using fixed effects or OLS with removing of fixed effects using transformation of variables. However, the estimation results using the OLS regression may suffer from Nickell bias for large datasets (Sigmund and Ferstl, 2019). Therefore, they suggest using the GMM framework for estimators of the panel VAR model.

3.2.1 GMM estimation

The GMM estimation for the panel VAR model estimates is proposed by Sigmund and Ferstl (2019) and Abrigo and Love (2016). Using the GMM approach, the estimates of panel VAR are consistent for a large number of cross-sections (Abrigo and Love, 2016).

In the GMM framework, the unobserved individual effect can be eliminated using the first difference (FD) of forward orthogonal deviation (FOD). Abrigo and Love (2016) point out that the first difference transformation may cause a significant observation removal for an unbalanced panel. They claim that the forward orthogonal deviation transformation is more suitable for an unbalanced panel as it does not cause missing observations in the dataset. In the FOD transformation, the average from all observations in future which are available is subtracted. Kazuhiko (2009) also suggests the FOD transformation as the results of simulation for GMM estimator with FOD transformation showed better performance.

Using the FOD transformation, the new variables have the following form

$$m_{it}^* = (m_{it} - \overline{m_{it}})\sqrt{T_{it}/(T_{it}+1)},$$

where m_{it} stands for the original variables. (Abrigo and Love, 2016)

Hansen (1982) and Abrigo and Love (2016) define the GMM estimator as the following:

$$A = (\widetilde{Y^*}' Z\widehat{W}Z'\widetilde{Y^*})^{-1}(\widetilde{Y^*}' Z\widehat{W}Z'Y^*),$$

where $Y_{it}^* = \begin{bmatrix} y_{it}^{1*} & y_{it}^{2*} & \dots & y_{it}^{k-1*} & y_{it}^{k*} \end{bmatrix}$, $\widetilde{Y^*} = \begin{bmatrix} Y_{it-1}^* & Y_{it-2}^* & \dots & Y_{it-p+1}^* & Y_{it-p}^* & X_{it}^* \end{bmatrix}$, $\widehat{W}$ is weighting matrix, Z is a row vector of instruments.

3.2.2 Estimation process

The estimation process of the panel VAR requires several steps to ensure that the model will be specified correctly and that results will not be biased. Firstly, the data have to be stationary due to their nature. Then, the cointegration test has to be performed if a non-stationary variable is detected. Additionally, the selection of optimal lag length is very important for the panel VAR model.

Cross-sectional Dependence

The panel data should be checked to determine whether there is a cross-sectional dependence. The cross-sectional dependence of errors could arise, for example, because of spatial effects, omitted common effects (Pesaran, 2015).

This assumption of cross-sectional dependence is verified before the assumption of stationarity.

The cross-sectional dependence can be checked using the CD test performed by Pesaran (2004):

$$CD_P = \sqrt{\frac{2T}{N(N-1)}}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij}\right),$$

where i=1,2,..., N, t=1,2,...,T, $\hat{\rho}$ states for the sample estimate of the pair-wise correlation of residuals:

$$\hat{\rho}_{ij} = \hat{\rho}_{ji} = \frac{\sum_{t=1}^{T}\hat{u}_{it}\hat{u}_{jt}}{(\sum_{t=1}^{T}\hat{u}_{it}^2)^{1/2}(\sum_{t=1}^{T}\hat{u}_{jt}^2)^{1/2}}, \qquad \text{for } i \neq j.$$

The formula of the CD test above is suitable for balanced panel data. For the unbalanced panel, Pesaran (2004) proposed an adjusted version of the CD test, which has the following form:

$$CD_P = \sqrt{\frac{2}{N(N-1)}}\left(\sum_{i=1}^{N_1}\sum_{j=i+1}^{N}\sqrt{T_{ij}}\hat{\rho}_{ij}\right),$$

where T_{ij} is the number of elements in the set of $T_i \cap T_j$.

The null hypothesis of the Pesaran CD test assumes no cross-sectional dependence. In other words, $\hat{\rho}_{ij}$ and $\hat{\rho}_{is}$ are not correlated for all $i \neq j \neq s$. (Pesaran, 2014)

The Pesaran CD test was also performed by Kocisova and Pastyrikova (2020) for testing cross-sectional dependency in panel data.

Determining the cross-sectional dependence in data is essential for unit root testing. Since some unit root tests are based on the assumption of independence, the results of those unit root tests may not be correct.

Stationarity

Before the estimation of the panel VAR model, the assumption of stationarity of variables has to be checked. The presence of stationarity is crucial; otherwise, the non-stationary variables could suffer from the unit root. Moreover, Kocisova and Pastyrikova (2020) argue that panel data that are not stationary can cause that the results can be misinterpreted.

The stationarity can be tested using several tests. There are two groups of unit root tests - the first generation and the second generation panel unit root tests. The appropriate tests are chosen based on the results of the cross-sectional dependence test. The first generation panel unit root tests are suitable for data that are cross-section independent. On the contrary, the second generation panel unit root tests allow the dependence across individuals. Therefore, they are suitable for data that are cross-sectionally dependent.

The first generation panel unit root tests include, for example, the panel unit root test by Im, Pesaran and Shin (2013), which was used by Ghosh (2017). Another test that assumes cross-sectional independence is the Maddala Wu test which was used for stationarity testing by Kosicova and Pastyrikova (2020) and Kjosevski and Petkovski (2017). Levin-Lin-Chu test is another widely used first generation unit root test.

The group of the second generation panel unit root test does not require the assumption of independence. The GLS test, a test based on panel corrected standard errors, can be used for stationarity testing. Moreover, Pesaran (2007) proposes to use the CIPS panel unit root test, which is based on the cross-section augmented Dickey-Fuller (CADF) statistics. Another possible test for unit root is the CADF test by Hansen. The CADF test is based on this regression:

$$\Delta y_{it} = a_i + \phi_i y_{i,t,-1} + b_i \overline{y}_{t-1} + c_i \Delta \overline{y}_t + e_{it},$$

where , $\overline{y}_t = N^{-1} \sum_{i=1}^{N} y_{it}$, $\Delta \overline{y}_t = N^{-1} \sum_{i=1}^{N} \Delta y_{it} = \overline{y}_t - \overline{y}_{t-1}$.

The Pesaran CIPS test has the following form:

$$CIPS = N^{-1} \sum_{i=1}^{N} CADF_i,$$

where $CADF_i$ is the test statistics of CADF statistics for i.

The null hypothesis for the CADF test and Pesaran CIPS test suggest that the unit root is present in the data.

Cointegration

The cointegration test serves to investigate the stable long-run relationship between non-stationary variables.

The cointegration attribute can be investigated using several approaches. For examining cointegration in the panel VAR model, the Johansen Cointegration test can be used (Nkusu, 2011; Beaton, Myrvoda and Thompson, 2016). Another approach that could be used to reveal cointegration among variables is the Engle-Granger based Kao's residual test (Ghosh, 2017). Additionally, the cointegration test by Westerlund (2007) is another approach for detecting cointegration between variables based on examining the error term from the error-correction model.

Lag length

For estimating the panel VAR model, one of the most crucial issues is to choose the right lag length. Canova (2007) proposes to determine the lag length based on a likelihood ratio (LR) test or using information criteria: Akaike Information Criterion (AIC), Hannan and Quinn Information Criterion (HQIC), and Bayesian Information Criterion (BIC). Those information criteria do not look at the in-sample fit of models, but they minimize the forecast error; thus, they are more appropriate to use for forecasting.

Abrigo and Love (2016) and Sigmund and Ferstl (2019) suggest using the lag length based on a methodology proposed by Andrews and Lu (2001), the moment and model selection criteria (MMSC) for GMM models. This approach of lag length selection is based on the J statistic of overidentifying restrictions. This MMSC approach can be applied for information criteria that were stated previously - AIC, BIC and HQIC. Those criteria are defined as follows:

$$MMSC_{BIC,n}(b,c,) = J_n(b,c,) - (|c| - |b|) * ln(n)$$

$$MMSC_{AIC,n}(b,c) = J_n(b,c) - (|c| - |b|) * 2$$

$$MMSC_{HQIC,n}(b,c) = J_n(b,c) - Q * (|c| - |b|) * ln(ln(n)),$$

where $J_n(b,c)$ is the overidentification test statistics proposed, c represents the number of conditions, b represents the number of parameters, and n states for the number of observations. (Sigmund and Ferstl, 2019)

Hansen overidentification test

Sigmund and Ferstl (2019) emphasize the importance of the exogenous instruments assumptions in GMM estimation. Hansen overidentification test serves as a test for verifying the assumption of exogenous instruments. The Hansen overidentification statistic has the following form:

$$N(\frac{1}{N}\sum_{i=1}^{N} Z_i\hat{E}_i)^T \Lambda_{z_{\hat{e}}}^{-1}(\frac{1}{N}\sum_{i=1}^{N} Z_i\hat{E}_i) \overset{a}{\sim} \tilde{\chi}^2_{L-K},$$

where L represents the number of instruments, K represents the number of parameters in the model, $\Lambda_{z_{\hat{e}}}$ indicates that two-step GMM estimation was used, Z_i represents a product of instrument matrix and the number of exogenous variables, $\hat{E}_i$ represents the fitted values with one-step estimation.

The formula above is also often called the Hansen J statistic. The Hansen J statistic is used for the lag length selection using MMSC for GMM models by Andrews and Lu (2001).

The null hypothesis in the Hansen overidentification test is that the instruments are exogenous. Therefore, the estimated model is correct. Hence, the failure of the rejection of the null hypothesis is necessary for the right model specification.

Stability

The stability of the panel VAR model determines the invertibility of the model and the feature of an infinite-order vector moving-average (VMA) representation (Abrigo and Love, 2016).

The stability of the model can be determined using the modulus of eigenvalues of the model. The model can be indicated as stable if all absolute values of the companion matrix A are lover than one (Abrigo and Love, 2016; Sigmund and Ferstl, 2019). The companion matrix is formed from the alternative representation of the VAR(p) model - the companion form of the VAR(p) model, which is the following:

$$Y_t := \begin{bmatrix} y_t \\ y_{t-1} \\ y_{t-2} \\ \vdots \\ y_{t-p+1} \end{bmatrix}, U_t := \begin{bmatrix} u_t \\ 0 \\ \vdots \\ 0 \end{bmatrix} A := \begin{bmatrix} A_1 & A_2 & \cdots & A_{p-1} & A_p \\ I_K & 0 & \cdots & 0 & 0 \\ 0 & I_K & \cdots & 0 & 0 \\ \vdots & & \ddots & \vdots & \vdots \\ 0 & 0 & \cdots & I_K & 0 \end{bmatrix}$$

According to Lütkepohl (2005), the stability of VAR(p) is satisfied if the following holds:

$$det(I_K p - Az) \neq 0 \text{ for } |z| \leq 1.$$

Abrigo and Love (2016) claim that the stability of the panel VAR model is important for impulse responses functions which are used for investigating the feedback effects of NPL.

3.3 Impulse Response Function

Impulse response functions (IRF) are often used to interpret the VAR model. They show the response of variable to shock while holding all other shocks equal to zero (Love and Zicchino, 2006).

There are two types of impulse response functions - the orthogonal IRF and the generalized IRF.

Orthogonal impulse responses function

The orthogonal IRF (OIRF) were used by Kjosevski and Petkovski (2017), Us (2020) and Nkusu (2011).

For VAR(p) model

$$y_t = \theta_1 y_{t-1} + \theta_2 y_{t-2} + ... + \theta_p y_{t-p} + u_t \quad u_t \sim IID(0, \Sigma)$$

where y_t is m×1 vector, θ_i are m× m matrices of coefficients, and Σ is the covariance matrix of error terms.

Pesaran (2015) proposes to rewrite the above equation of the VAR(p) model into an infinite-order moving average (MA) representation:

$$y_t = \sum_{j=0}^{\infty} A_j u_{t-j}.$$

Then for the IRF, the implementation of Cholesky decomposition is used. The Cholesky decomposition makes variables that stand earlier in the ordering more exogenous and variables that stand later in ordering more endogenous. One of the main drawbacks of using the Cholesky decomposition is that it depends on the ordering of variables. By applying the Cholesky composition to the covariance matrix of error terms Σ, the following term will be obtained:

$$\Sigma = PP',$$

where P is a lower-triangular matrix. Then, the MA representation of VAR(p) is rewritten to

$$y_t = \sum_{j=0} B_j \eta_{t-j}, \qquad B_j = A_j P, \quad \eta_t = P^{-1} u_t.$$

Using this equation, the orthogonalized IRF of a shock to the i$^{\text{th}}$ variable on the j$^{\text{th}}$ variable is defined as

$$OI_{ij,n} = e_j' A_n P e_i, \quad i, j = 1, ..., m,$$

where P is a lower-triangular matrix, e_j is a selection vector with the following form:

$$e_i = \begin{pmatrix} 0 \\ 0 \\ \vdots \\ 1 \\ \vdots \\ 0 \\ 0 \end{pmatrix}$$

where 1 is on the i-th position of the selection vector. (Pesaran, 2015)

Generalized impulse responses function

In the generalized impulse responses function (GIRF), the ordering of variables does not matter. This feature of invariant variables ordering is a big advantage of GIRF. The generalized impulse responses functions are also widely used. They were used by, for example, Anastasiou et al. (2016b) and Ghosh (2017).

When constructing the GIRF, there is a shock to the r-th element and the effect of the shock is integrated using the distribution of errors.

The Sigmund and Ferstl (2019) defines the GIRF as following:

$$GIRF(k, r, \Sigma_\epsilon) = A^k \Sigma_\epsilon (\sigma_{r,r})^{-\frac{1}{2}},$$

where r is the element exposed to shock, k is the number of periods, Σ_ϵ is a covariance matrix of ϵ_t, $\sigma_{r,r}$ is the r-th diagonal element of Σ_ϵ.

Confidence intervals for impulse response functions

The confidence bands for the GIRF and OIRF can be obtained by temporal resampling, cross-sectional resampling and a combined resampling when using panel data (Sigmund and Ferstl, 2019). In this analysis, cross-sectional resampling will be used, as Sigmund and Ferstl (2019) suggested.

In the cross-sectional resampling, the bootstrapping procedure proposed by Kapetanios (2008) starts with drawing subsets from the original dataset N-times with replacement. Each of these subsets contains the same panel individual. After, the estimation on the subset by the predetermined GMM method is done. The last step is the calculation of the impulse response functions (generalised or orthogonal).

3.4 Local Projections

The method of Local projections (LP) is an alternative to the estimation of impulse response functions. The paper by Jordà (2005), which introduced the method of local projections, has become popular. In the LP approach, the parameters are estimated at each point of interest as opposed to IRF generated by the VAR method (Adämmer, 2019).

Adämmer (2019) points out that the estimation of IRF by LP is easier. Moreover, IRF generated by LP are more robust when the VAR model is not specified correctly.

Jordà (2005) defines the following ordinary least squares regression, which is estimated for each point of time:

$$y_{t+h} = \alpha^h + B_1^h y_{t-1} + ... + B_p^h y_{t-p} + u_{t+h}^h, \quad h = 0, 1, ..., H-1,$$

where α^h stands for a vector of constant, B are matrices of parameters, p denotes lag, h stands for a forecast horizon.

Then, the impulse responses have a following form:

$$I\hat{R}(t, h, d_i) = \hat{B}_1^h d_i, \quad d_i = B_0^{-1}.$$

The process of the estimation of IRF using LP method is suitable for panel data. Adämmer (2019) specified the equation for panel data as the following:

$$y_{i,t+h} = \alpha_{i,h} + shock_{i,t,}\beta_h + s_+ x_{i,t}\gamma_h + \epsilon_{i,t+h}, \quad h = 0, 1, .., H-1,$$

where $\alpha_{i,h}$ captures the fixed effect and $x_{i,t}$ is a vector of control variables.

Chapter 4

Data

The dataset used for analysis covers an unbalanced panel of banks located in the countries of EMU. The dataset contains variables from the macroeconomic sector and the banking sector that serves as determinants of NPL. The source of bank sector data is The Banker database. The macroeconomic data are taken from the Organization for Economic Cooperation and Development (OECD) database, and the volatility index VSTOXX is from Investing.com. The dataset sample covers data on annual frequency from 2004 to 2020 for a sample of 17 out of 19 Economic and Monetary Union members (i.e. Austria, Belgium, Estonia, Finland, France, Germany, Greece, Ireland, Italy, Latvia, Lithuania, Luxembourg, Netherlands, Portugal, Slovakia, Slovenia, Spain)[1].

For the purpose of determining the existence of financial fragmentation, countries were split into two groups: core and periphery countries. Austria, Belgium, Estonia, France, Germany, Finland, Latvia, Lithuania, Luxemburg, Netherlands, and Slovakia were labelled as core countries. Greece, Italy, Ireland, Portugal and Spain, and Slovenia were included in the group of periphery countries. This division was made based on Anastasiou et al. (2016b) and Bartlett and Prica (2017).

The selection of variables used in the analysis was made based on the literature review. Bank-specific and macroeconomic variables were included. As bank-specific variables, NPL ratio, ROA, and loan to deposit ratio were included. As macroeconomic variables, GDP growth, government deficit, unemployment rate, current account balance, and risk aversion were included. The summary statistics of variables used in the analysis can be found in Table 4.1.

The description of each variable used in further analysis follows.

[1] Malta and Cyprus are not included in the sample because of large unavailability of data

Table 4.1: Descriptive Statistics

Variable	Mean	St. Dev.	Min	Median	Max
NPL ratio	5.541	6.063	0.100	3.700	39.500
ROA	0.430	1.274	−15.100	0.400	13.200
Loan to deposit ratio	103.766	25.171	35.100	100.800	177.700
GDP growth	0.975	3.678	−14.839	1.579	25.176
Government deficit	−2.809	3.752	−32.124	−2.444	5.108
Unemployment rate	9.184	4.627	3.150	8.100	27.492
Current account balance	1.338	5.238	−20.807	1.883	10.835
VSTOXX	22.937	6.571	14.045	23.586	33.729

Bank variables

The **non-performing loans ratio** is the ratio of gross NPL and gross total loans. The data for the NPL ratio were obtained from The Banker Database. The definition of NPL may vary; therefore, it is essential to state which definition the data source uses. The Banker database defines NPL as loans that are more than 90 days overdue with accruing interest. The gross NPL includes previously-defined loans (impaired and not impaired) and non-accrual loans. The NPL ratio is expressed in percentage values. Figure 4.1 shows the distribution of the NPL ratio in the dataset. It can be seen that most of the observation has the NPL ratio between 0 and 10. The development of the NPL ratio in individual countries of the EMU is depicted in Figure 4.2. The graph suggests that the level of NPL varies across countries. An enormous instability can be seen in Greece, where there was a dramatic increase around 2010. It can also be seen that the level of NPL was declining at the end of the examining period.

Figure 4.1: Histogram of NPL ratio

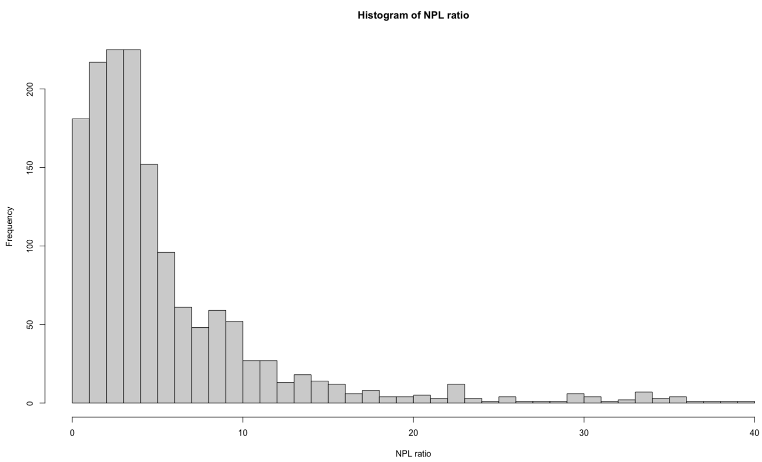
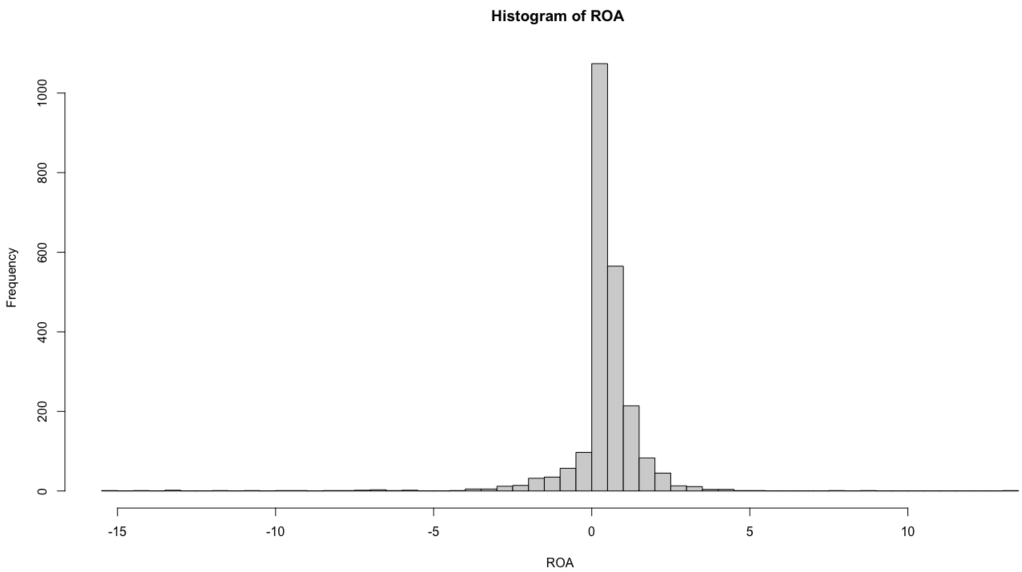


Figure 4.2: NPL ratio by country

Return on asset (ROA) is the ratio of net income and total assets. ROA serves as a profitability indicator that serves as a determinant influencing NPL. Figure 4.3 depicts a histogram of ROA that illustrates the distribution of ROA in EMU countries. It can be seen that the level of ROA fell into the interval between -5 and 5 for most of the observations.

Figure 4.3: Histogram of ROA



Loan to deposit (LTD) ratio is a ratio between gross total loans and gross total deposits. It also serves as an indicator of the liquidity risk of a bank. The low LTD ratio indicates high liquidity risk. The LTD shows how many loans a bank can cover with deposits. The optimal value of the ratio is 80% - 90%. If the ratio exceeds 100%, it means that the amount of provided loans exceeds the amount of accepted deposits by customers of the bank (Teplý and Tripe, 2005). The histogram in Figure 4.4 represents the distribution of the LTD ratio in the dataset. It can be seen that the LTD ratio fell into the interval between 50 and 150 for most of the observations. Figure 4.5 shows the LTD ratio in the EMU countries over a 17-year period from 2005 to 2021. Overall, the LTD ratio is continuously declining from 2008 to 2021. It can also be seen that the LTD ratio exceeds the value of 100 % for almost the whole selected period in the euro area. Some observations for the LTD ratio were indicated as outliers using the interquartile range (IQR) method. Due to their extreme values, which could bias further results of analysis, those observations were removed from the sample.

Figure 4.4: Histogram of LTD ratio

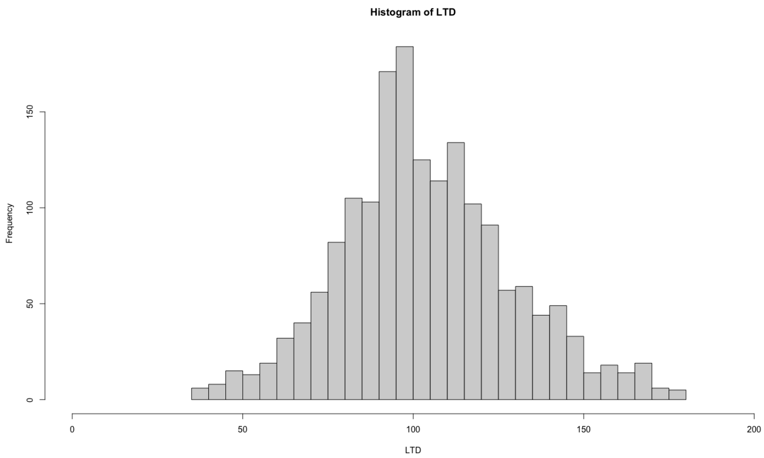
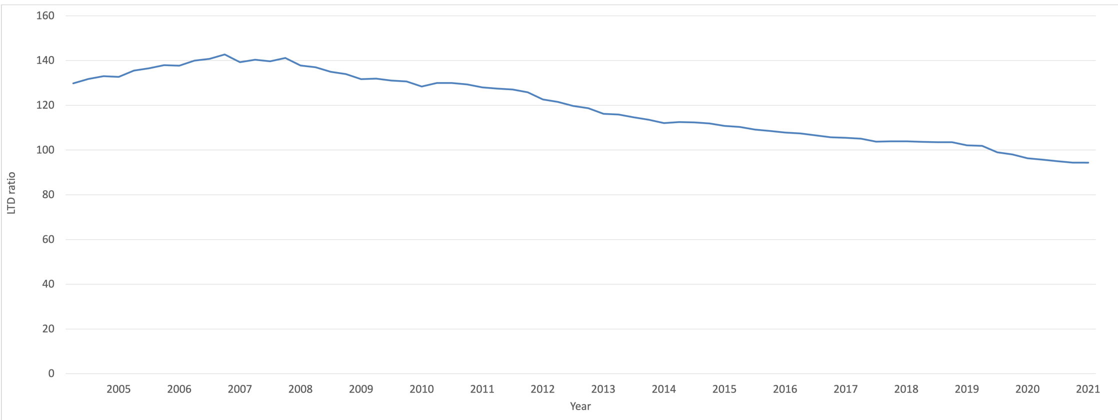


Figure 4.5: LTD ratio in Euro area

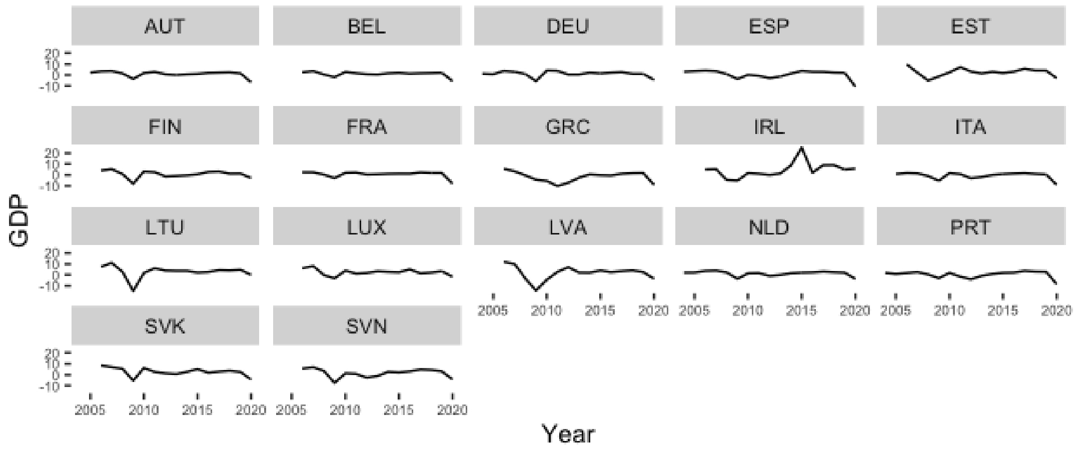


Source: https://www.euro-area-statistics.org/

Macroeconomic variables

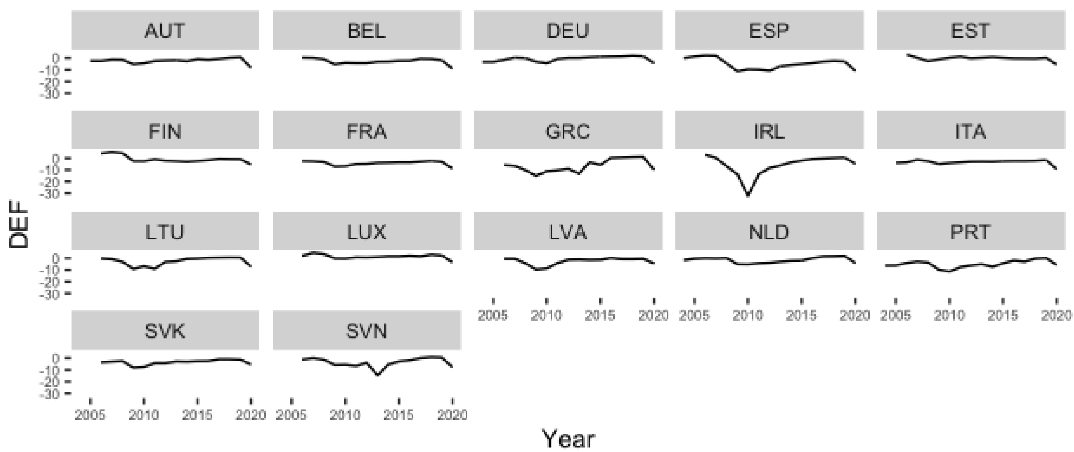
GDP growth as an indicator of economic activity belongs among the most important determinants of NPL, according to the literature review. GDP growth contrasts the change in the economic output from the last period (year in our case). As it was mentioned, we expect that the NPL suffers from countercyclical behaviour; therefore, the expected sign of a relationship with NPL is negative. Figure 4.6 shows GDP growth in individual countries. Negative GDP growth can be seen in all countries during the Great Recession around 2008. The second significant drop in GDP growth can be seen in 2020 because of the COVID-19 pandemic in the world.

Figure 4.6: GDP growth by country



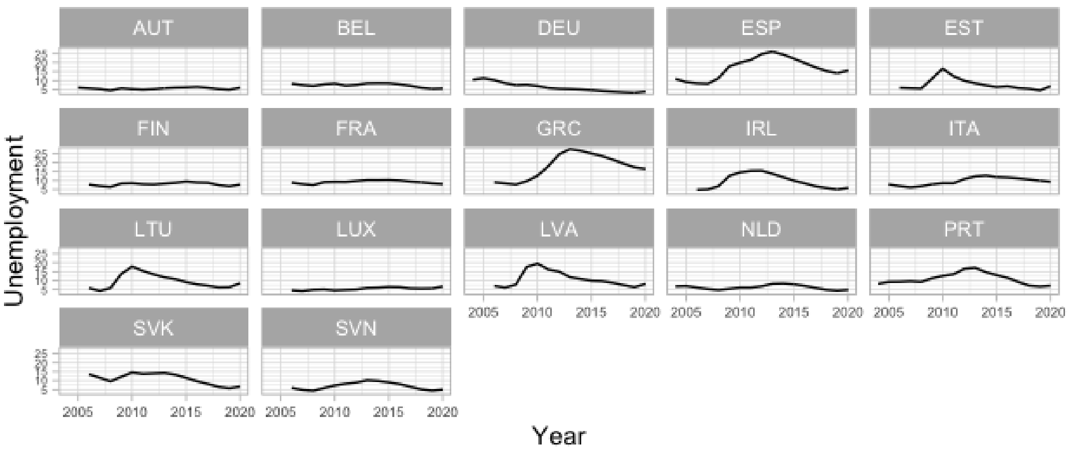
A Government deficit is characterized as a difference between the income and expenditures of a government. A positive value of this difference signalizes that the government has a surplus, and the government can be marked as a net borrower. On the other hand, in case of a negative difference between income and expenditures, the government has a deficit, and it can be referred to as a net lender. The evolution of government deficit in individual EMU countries is depicted in Figure 4.7. The figure shows two markable declines in all countries connected to two crises in the period between 2005 and 2020. The expected reaction to a shock in NPL to the government deficit is ambiguous. Bilan (2015) suggests a positive sign of a budget balance, and Anastasiou et al. (2016b) propose that the sign can be either negative or positive.

Figure 4.7: Government deficit by country



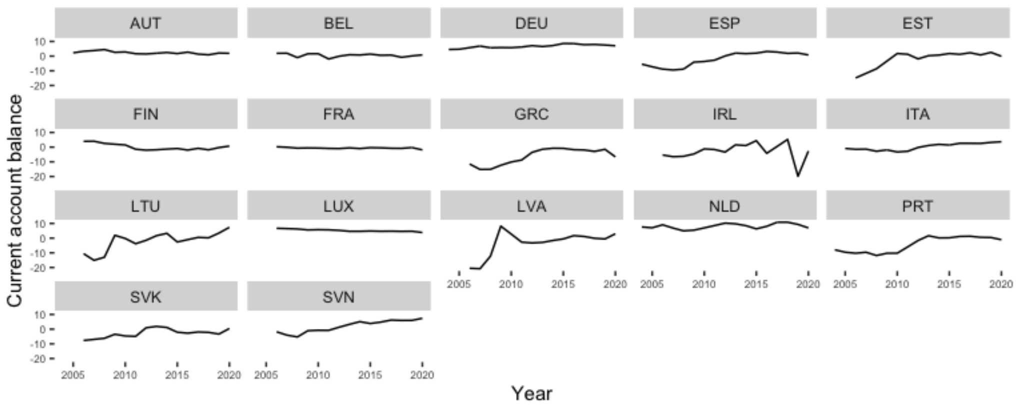
The unemployment rate represents the ratio of unemployed people and the labour force. Unemployed people are people of working age who do not have a job. The labour force includes employed and unemployed people. The variable of the unemployment rate is seasonally adjusted. Figure 4.8 shows the evolution of unemployment in Eurozone countries. At first glance, the unemployment rate in the EMU countries is relatively low for most of the countries (Austria, Belgium, Germany, Finland, France, Luxembourg, Netherland, Slovakia, Slovenia). However, we can see that the unemployment rate suffered a sharp rise in Estonia, Spain, Greece, Lithuania, Latvia and Ireland during the period 2004-2020. It is expected that the higher unemployment rate increases the NPL ratio.

Figure 4.8: Unemployment by country



Current account balance is a variable that captures international financial flows (Staehr and Uusküla, 2017). The current account balance captures all transactions between residents of the country and other non-residents. A positive current account balance signalises a growth of economic stability. The increase in current account balance signifies an increase in exports, which leads to economic growth. It is expected that with the increase of this determinant, the NPL should decrease (Kuzucu and Kuzucu, 2019). The current account balance is measured as a percentage of GDP. The development of the current account balance for individual Eurozone members is depicted in Figure 4.9. At first glance, it is visible that most of the countries in the euro area have stable current account balance ratio (e.g. Austria, Belgium, Germany, France, Finland, Italy, Luxembourg). However, some countries have unstable development of current account balance. For example, it can be seen that there was a significant drop in the current account balance in Ireland in 2020.

Figure 4.9: Current account balance by country



Risk aversion is the prioritization of certain proceedings over uncertain proceedings, which may be higher. The Chicago Board Options Exchange Market (CBOE) Volatility Index, known under its ticker label as the VIX index, is a widely used indicator of risk aversion. Many studies (e.g. Klein, 2015; Espinoza and Prasad, 2010) use the VIX index as an approximation of risk aversion. However, the VIX index is based on a calculation of the expected volatility of the S&P 500 Index, which includes 500 large companies listed on the stock exchange in the USA. In this thesis, the countries from the Eurozone are analysed. Therefore, the VSTOXX volatility index was found to be a more suitable indicator of risk aversion. The volatility index VSTOXX is measured as the 30-day implied volatility of the EURO STOXX 50 Index, which includes 50 companies from the euro area. A rise in the VSTOXX index indicates an increase in the level of uncertainty in the market. If we look at the trends of the development of the VSTOXX index over examined period illustrated in Figure 4.10, there was a rapid increase in risk aversion (i.e. rapid increase of the VSTOXX index) during the Great Recession between 2007 and 2009. Similarly, there was a rapid upsurge in 2019 when the COVID-19 pandemic hit the world. Moreover, the comparison of the VSTOXX index and the VIX index is depicted in Figure 4.11. It can be seen that the value of the VSTOXX index is higher than the VIX index during almost during almost the whole examined period. However, the trajectory line of those two volatility indices is similar.

Figure 4.10: VSTOXX Index

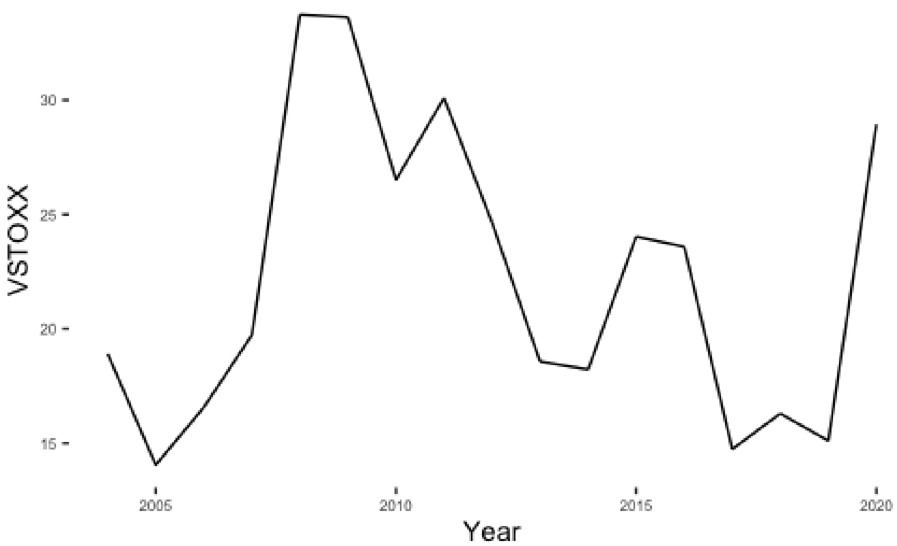
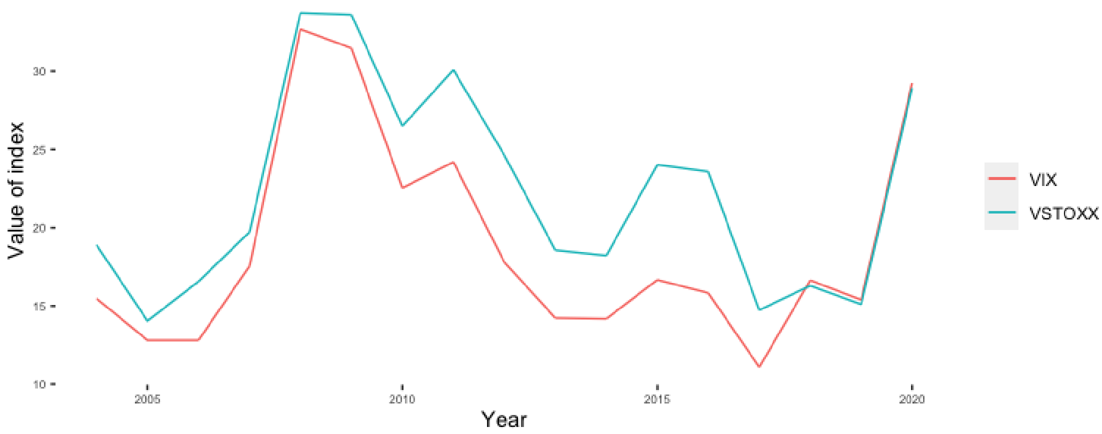


Figure 4.11: VSTOXX and VIX Index



Chapter 5

Econometric models and results

5.0.1 Model specification

We will analyse three models. Models will include variables which were described in the previous chapter. The first model includes only bank-specific determinants of NPL. The second model includes only macroeconomic factors of NPL. The third model includes both groups of determinants - bank specific and macroeconomic factors.

The estimated model has the following, which is proposed by Sigmund and Ferstl (2019):

$$y_{i,t} = \mu_i \sum_{l=1}^{p} A_l y_{i,t-l} + \epsilon_{i,t},$$

where $y_{i,t,}$ is an $m \times 1$vector of endogenous variables for ith cross-sectional unit at time t, $y_{i,t-l}$ is an $m \times 1$ vector of lagged endogenous variable.

For testing of financial fragmentation in EMU countries, the original dataset will be tested on two subsamples from the original sample based on the location of the individual banks. The first subsample will include only observations which are related to core countries. The second subsample consists of banks located in periphery countries. The process of estimation will be similar to the estimation process done for testing the whole sample. However, the generated generalized impulse response functions will be compared at the end to detect whether they are different for core and periphery countries.

5.1 Pre-estimation process

Prior to the estimation of panel VAR, the data properties have to be checked, as it was already mentioned previously. Those steps ensure that the estimation results will not be biased.

The first step is to check whether the data are cross-sectionally independent. Therefore, the Pesaran CD test was performed to detect possible cross-sectional dependence. The results of the test are in Table 5.1. The p-values for all variables are very close to 0. Therefore, there is strong evidence to reject the null hypothesis of no cross-sectional dependence.

Table 5.1: Results of the Pesaran CD Test

Variable	Test Statistic	P-value
NPL ratio	46.731	$< 2.2e\text{-}16$
ROA	27.303	$< 2.2e\text{-}16$
Loan to deposit ratio	56.904	$< 2.2e\text{-}16$
GDP growth	30.475	$< 2.2e\text{-}16$
Government deficit	28.194	$< 2.2e\text{-}16$
Unemployment rate	18.866	$< 2.2e\text{-}16$
Current account balance	4.3837	1.167e-05
VSTOXX	47.218	$< 2.2e\text{-}16$

The Pesaran CD test suggests that the cross-sectional dependence occurs in data. Due to this, the second generation panel unit root test is needed for stationarity testing. Therefore, the cross-section augmented Dickey-Fuller (CADF) test was performed. The results of the CADF test are in Table 5.2. Table 5.2 shows the results for all variables allowing one lag due to the selected number of lags in estimated models. According to the results, the null hypothesis of the presence of unit root in data can be rejected. Therefore, the data are stationary.

Table 5.2: Results of CADF Test

Variable	Test Statistic	P-value
NPL ratio	−8.985	3.625e-15
ROA	−25.377	< 2.2e-16
Loan to deposit ratio	−13.33	< 2.2e-16
GDP growth	−21.424	< 2.2e-16
Government deficit	−22.974	< 2.2e-16
Unemployment rate	−15.41	< 2.2e-16
Current account balance	−24.18	< 2.2e-16
VSTOXX	20.541	< 2.2e-16

The next step is the lag length selection. For this, the MMSC approach for GMM models by Andrews and Lu (2001) was used. The results of information criteria are in Table 5.3. We tested each model for a maximum of 4 lags.

Table 5.3: Lag length selection

Model	Lag number	MMSC BIC	MMSC AIC	MMSC HQIC
Full model	1	**-1524.903**	-359.4272	**-854.0059**
Full model	2	-1453.013	-378.5394	-840.139
Full model	3	-1378.17	-396.2418	-823.7053
Full model	4	-1330.443	**-444.3355**	-835.704
Macro model	1	**-1290.812**	-264.4259	**-695.4306**
Macro model	2	-1232.959	-274.7639	-681.4371
Macro model	3	-1187.829	-297.7666	-679.7589
Macro model	4	-1154.933	**-334.1787**	-690.6698
Bank model	1	**-843.1703**	-180.5408	**-461.7327**
Bank model	2	-807.8674	-190.0452	-455.465
Bank model	3	-764.8631	-193.4826	-442.2222
Bank model	4	-725.8858	**-203.7153**	-434.3432

The number of lags should be chosen based on the lowest value of the information criterion. We select the number of lags based on the results of the MMSC BIC and the MMSC HQIC. Sigmund and Ferstl (2019) suggest to prefer the MMSC BIC and the MMSC HQIC over the MMSC AIC. They claim that the MMSC AIC may not be consistent as there is a positive probability even asymptotically of selecting too few over-identifying restrictions (Andrews and Lu, 2001). Table 5.3 shows that for the full model, the MMSC BIC and MMSC HQIC has the lowest value of -1524.903 and -854.006, respectively, for one lag. Similarly, the lowest value of MMSC BIC and MMSC HQIC is for the model with one lag in the macro model and the bank model. Therefore, we will include one lag in further analysis.

The next step in the estimation process is to detect whether models fulfill the stability condition. For testing the stability, it has to be determined whether the modulus of eigenvalues of the model lies inside the unit circle. The results of the stability test are in Appendix A. All eigenvalues of all three models are inside the unit circle. Therefore, all three models are stable.

Finally, the performed Hansen overidentification test suggests that instruments used in our models are not correlated with residuals. Hence, the condition of exogenous instruments is fulfilled.

5.2 Results

All three models (full model, bank model, macro model) were estimated using a panel VAR approach. The panel VAR models were estimated using the two-step system GMM estimation with Windmeijer corrected standard errors. For all models, one lag of chosen variables was used for estimation due to the results of previous tests. Moreover, to reduce the number of instruments, the collapsing method was used. The collapsing method by Holz-Elkin was also used by Espinoza and Prasad (2010), Klein (2013) and Ghosh (2017). Furthermore, the forward orthogonal deviation was implemented to eliminate the unobserved individual effect. This method is more suitable for unbalanced panel data. The estimated panel VAR models are reported in Appendix A.

After the estimation of panel VAR models, generalized impulse response functions were estimated. For the GIRF estimation, the 95% confidence intervals were estimated. The confidence intervals were generated using the cross-sectional bootstrap method, which was discussed in Chapter 3.

5.2.1 GIRF

The generalized impulse response functions describe the reaction of one variable when the other variable is exposed to a positive shock. In our analysis, the magnitude of the shock is one standard deviation. For the estimation, the 95% confidence band was used. The GIRF for the model with all variables is reported in this section below. The full results for this model are presented in

Figure B.1 and Figure B.2 in Appendix B. The GIRF for the model with bank and macro variables separately can be found in Appendix B.

The GIRF for the model with all variables reported below are not significant within a 95% confidence interval. However, the results are supported with the results of models with bank-specific and macroeconomic variables separately. In those models, the responses of variables to shocks in other variables are significant in most cases.

Anastasiou et al. (2016b) investigated the feedback effect for ten quarters (i.e. 2,5 years). However, the response to the shock in the long run is important for the economy. Therefore, we focus on the long-run effect, and the generalized impulse response functions are estimated for a 7-years period.

Figure 5.1: Generalized impulse response functions
(a) Shock to NPL ratio response of GDP growth (left)
(b) Shock to GDP growth, response of the NPL ratio (right)

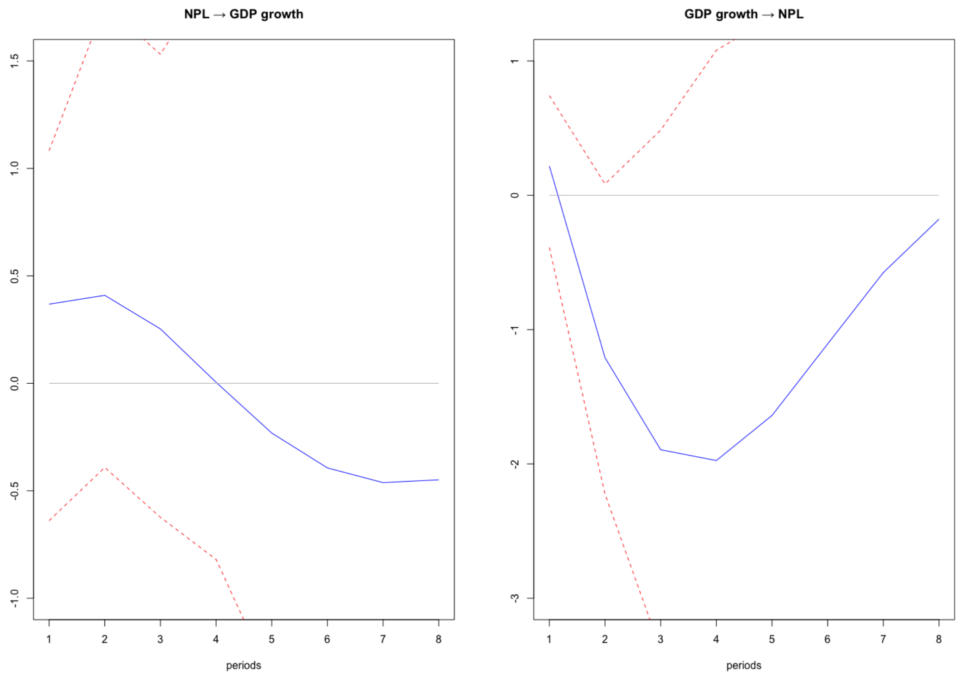
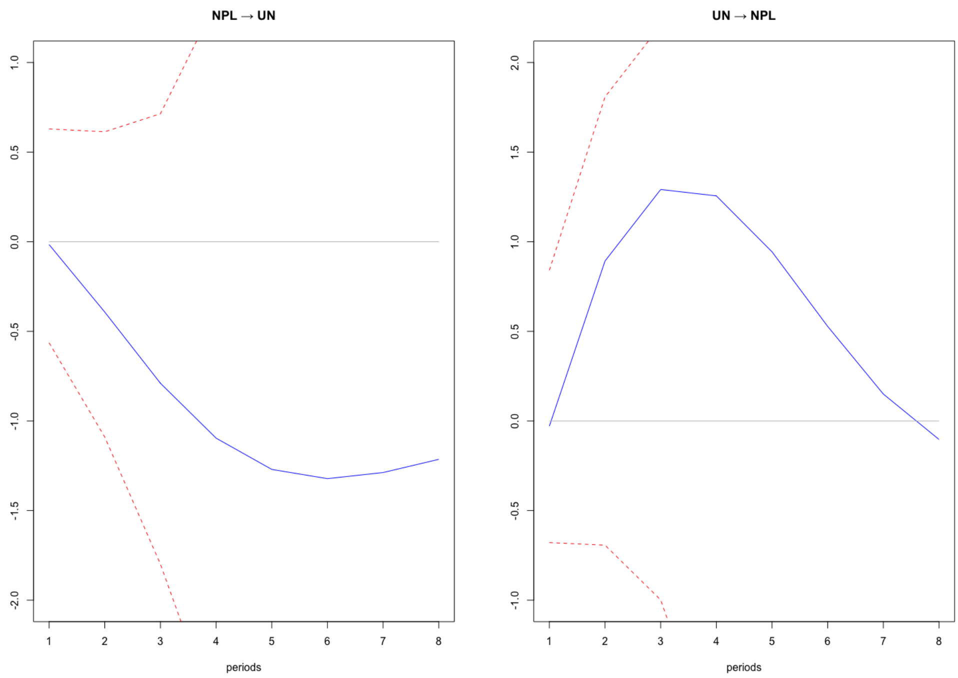


Figure 5.1 captures the generalized impulse responses for the NPL ratio and GDP growth. The graph on the left side shows the response of GDP growth to a shock in the NPL ratio. The graph on the right side depicts the reaction of the NPL ratio to a shock in GDP. The results suggest that a one-standard deviation shock to NPL causes an immediate increase in GDP growth. After, the GDP growth starts declining, and it crosses the zero line in the third period

after the shock. After that, the fall of the GDP growth slows in the seventh period after the shock. The shock seems to be persistent.

The response of the NPL ratio to a shock in GDP growth is overall negative. The NPL ratio reaches a low point in the third period after the shock. Then, it starts slowly returning to its original value. This result is supported by the economic theory. The response of the NPL ratio supports its countercyclical behaviour. This result is in line with the results of Us (2020), who detected a negative response of NPL to a GDP shock. Moreover, Klein (2013) obtained a similar response of NPL after a positive shock to GDP growth.

Figure 5.2: Generalized impulse response functions
(a) Shock to NPL ratio response of the unemployment rate (left)
(b) Shock to the unemployment rate, response of the NPL ratio (right)

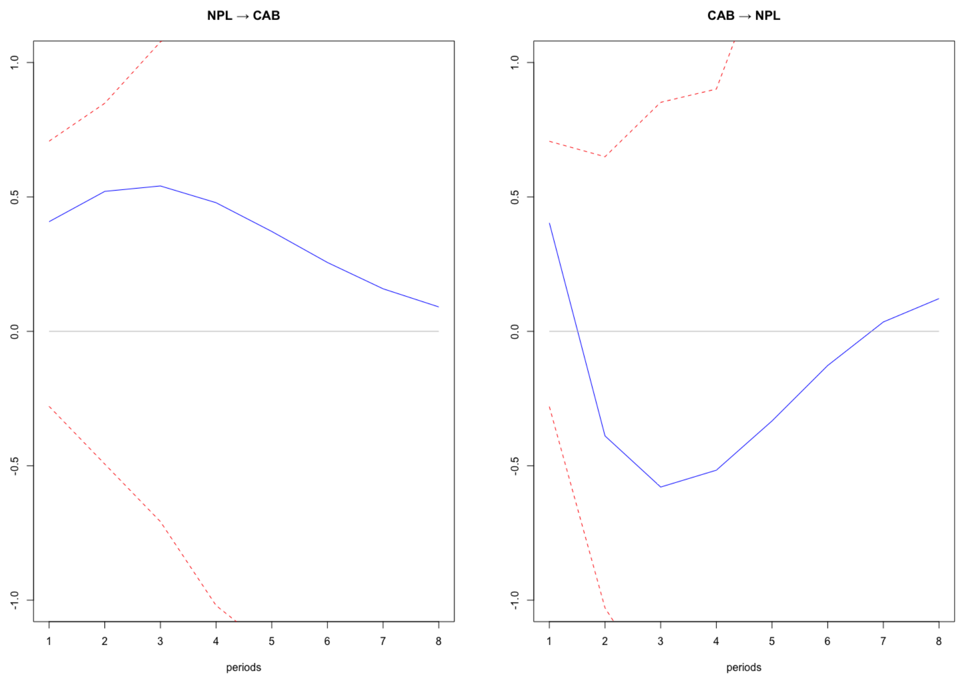


Note: The dashed lines indicate 95% confidence interval.

From Figure 5.2, which captures the GIRF between the NPL ratio and the unemployment rate, it can be seen that the shock to the NPL ratio leads to an immediate decrease in the unemployment rate. The unemployment rate decreases substantially over four periods. In the sixth period after the shock, the unemployment rate decreases by 1.32 percentage points. This result contradicts the economic theory. However, an alternative explanation of this effect may be that the higher level of NPL may force the unemployed debtor to find a job to repay his loans. This response is also supported by the results of the model with macroeconomic variables.

A positive shock to the unemployment rate causes a quick increase in the NPL ratio. The NPL ratio increases rapidly after a shock. The response reaches a peak in the third period when the NPL ratio rises by 1.29 percentage points. Then the response starts declining. This result is in line with the economic intuition. As the unemployment rate increases, more people are unemployed. Thus, the ability to repay a loan for unemployed people is lower. Moreover, the findings of Us (2020) and Kjosevski and Petkovski (2017) support those results.

Figure 5.3: Generalized impulse response functions
(a) Shock to NPL ratio, response of Current account balance (left)
(b) Shock to Current account balance, response of the NPL ratio (right)

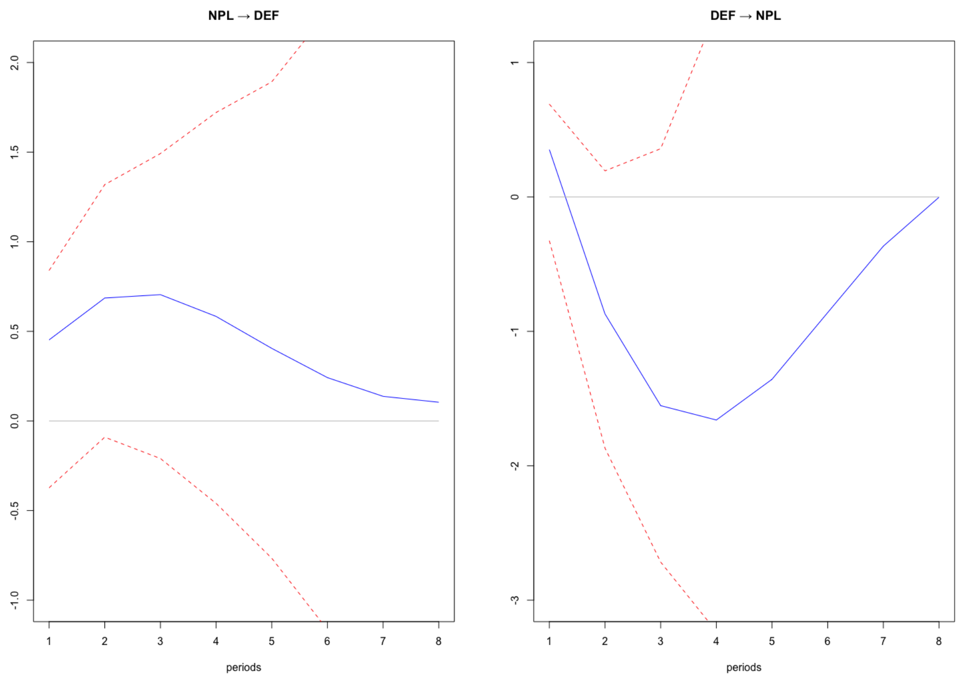


Note: The dashed lines indicate 95% confidence interval.

GIRF between the NPL ratio and the current account balance are depicted in Figure 5.3. The response of the current account balance to a shock in the NPL ratio is positive. There is an immediate increase of 0.407 percentage points in the current account balance in the first year. After the second year, the response converges slowly to zero.

On the contrary, the current account balance shock causes a rapid decrease in the NPL ratio during the first year. The response of the NPL ratio bottoms out in the second period after the shock, then it rises towards 0 and reaches the zero line during the sixth year after the shock. This result is in line with the theory of Kuzucu and Kuzucu (2019), who claims that an increase in the current account balance causes an export increase leading to an improved economic situation in the country and a decrease in the NPL.

Figure 5.4: Generalized impulse response functions
(a) Shock to NPL ratio, response of the government deficit (left)
(b) Shock to the government deficit, response of the NPL ratio (right)

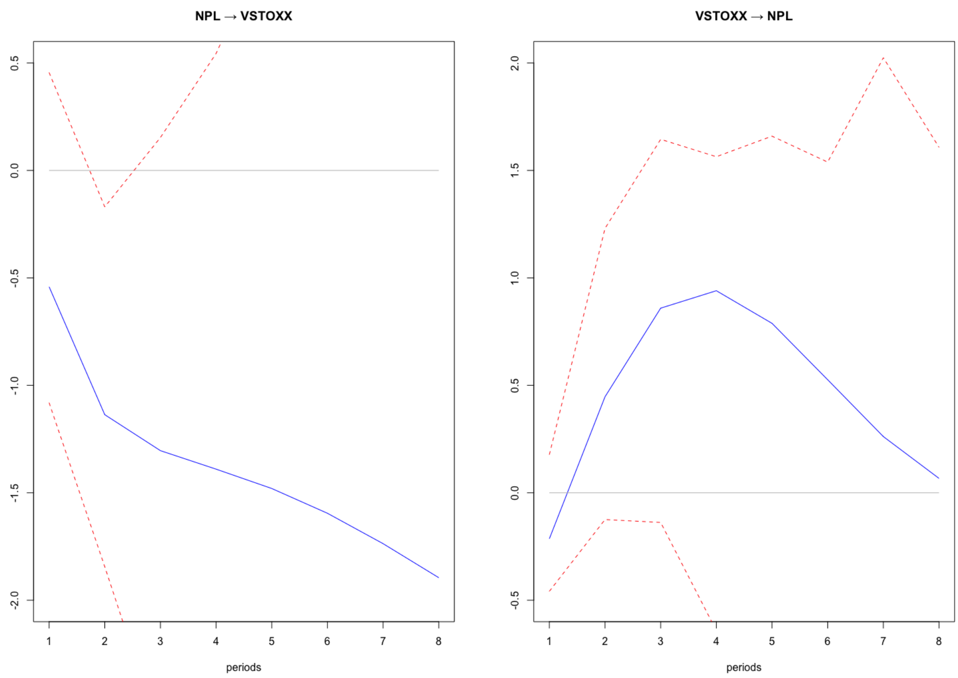


Note: The dashed lines indicate 95% confidence interval.

Figure 5.4 provides the GIRF between the NPL ratio and the government deficit. According to the literature review, the relationship between the government deficit and the NPL ratio is ambiguous. Our results suggest that a one standard deviation increase in the NPL ratio has a positive response to the government deficit. By magnitude, the shock to the NPL ratio leads to an increase in the government deficit by 0.452 percentage points. This shock is not permanent as it slowly converges to zero. However, it does not reach zero during the 7-years examined period.

The shock to the government deficit affects the NPL ratio negatively. Immediately after the shock, the NPL ratio increases. However, it is followed by a rapid drop in the NPL ratio. The NPL ratio reaches the bottom in the third period when the NPL ratio decreases by 1.659 percentage points. After, it starts slowly converging back towards to the zero line. In the seventh period after the shock, the response of the NPL reaches almost zero (more precisely, it declines only by -0.002 percentage points). This result is similar to the results by Anastasiou et al. (2016b), who obtained an immediate decrease in the NPL ratio after a positive shock to the government budget deficit. However, our results suggest that the effect of the NPL response lasts for a longer period.

Figure 5.5: Generalized impulse response functions
(a) Shock to NPL ratio, response of VSTOXX (left)
(b) Shock to VSTOXX, response of the NPL ratio (right)

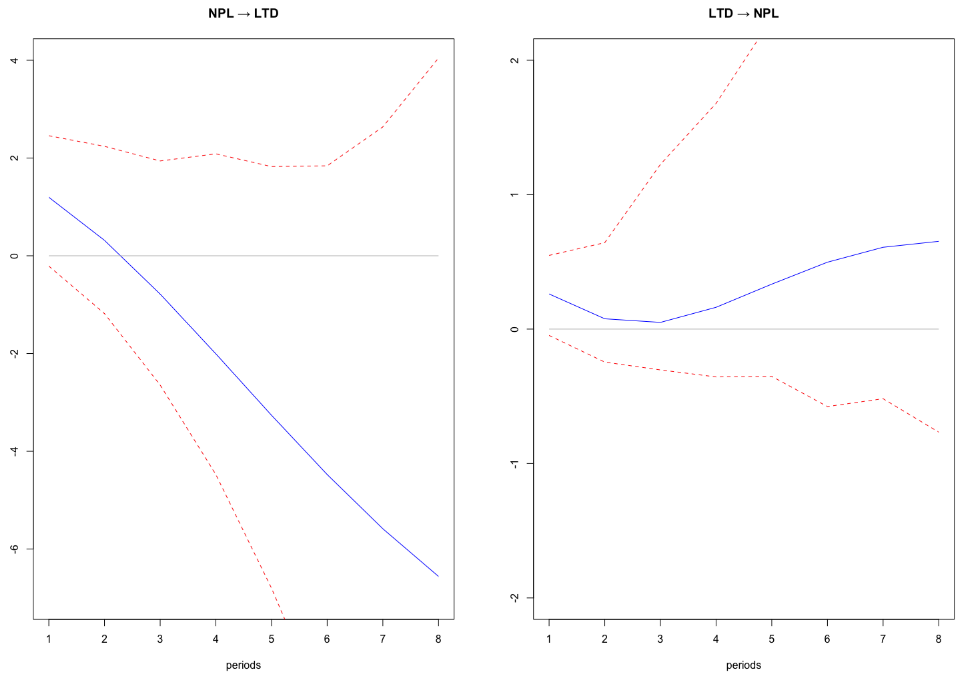


Note: The dashed lines indicate 95% confidence interval.

Figure 5.5 depicts the GIRF between the NPL ratio and the VSTOXX index, which is used as an indicator of risk aversion. The graph suggests that the positive shock to the NPL ratio immediately decreases risk aversion. Moreover, the VSTOXX index decreases gradually after the shock to NPL ratio.

A positive shock to risk aversion causes an increase in the NPL ratio. Immediately after a shock, a NPL ratio decreases; however, then it starts gradually increasing. The response reaches a peak in the third year after a shock. Then, it starts declining towards zero. An increase in the NPL ratio after an increase in VSTOXX was expected. Klein (2013) suggests that the higher volatility index may cause rates to be higher in the international financial market; therefore, borrower has a lower ability to repay the loan.

Figure 5.6: Generalized impulse response functions
(a) Shock to NPL ratio, response of loan to deposit ratio (left)
(b) Shock to loan to deposit ratio, response of the NPL ratio (right)

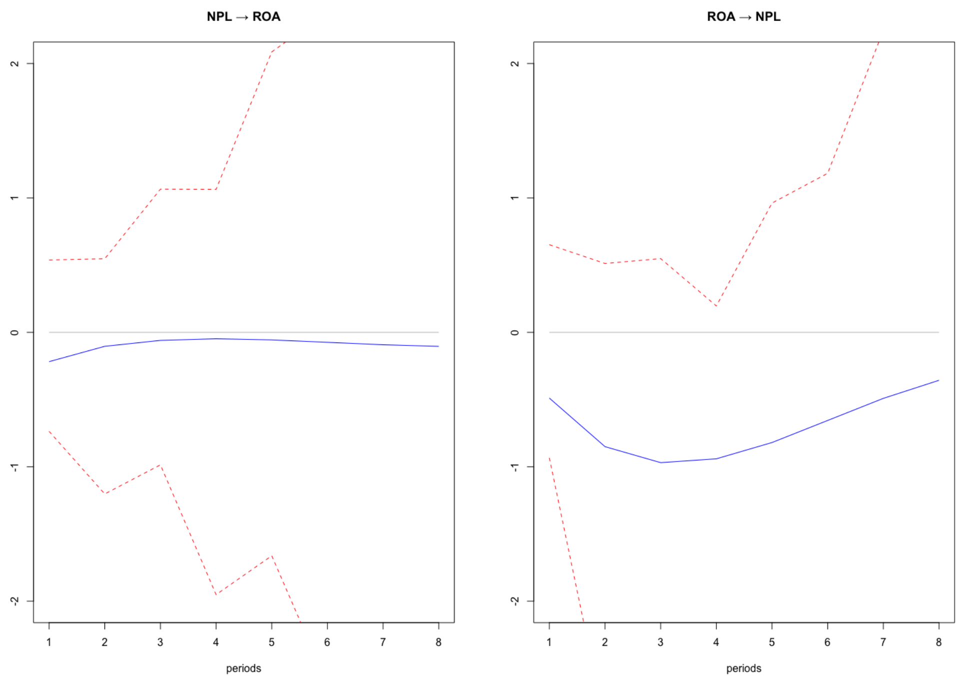


Note: The dashed lines indicate 95% confidence interval.

GIRF between the NPL ratio and the loan to deposit ratio are depicted in Figure 5.6. It can be seen that a positive increase in the NPL ratio is negatively related to the loan to deposit ratio. Immediately after a shock, the loan to deposit ratio increases. Then, it starts falling moderately. However, this effect cannot be supported by the result of the bank model, which suggests the opposite effect. Therefore, the effect of the loan to deposit ratio response is ambiguous.

The graph on the right side suggests that a positive shock to the loan to deposit ratio causes an increase in the NPL ratio. It can be seen that after an immediate increase in the NPL ratio, a fall in the response follows. However, the NPL ratio starts rising again in the third period after a shock. These results are supported by Anastasiou et al. (2016b), who detected an increase in NPL after a positive shock to the loan to deposit ratio.

Figure 5.7: Generalized impulse response functions
(a) Shock to NPL ratio, response of ROA (left)
(b) Shock to ROA, response of the NPL ratio (right)



Note: The dashed lines indicate 95% confidence interval.

The responses to shocks between the NPL ratio and ROA are captured in Figure 5.7. The response of ROA to a positive shock to the NPL ratio is negative. It can be seen that the magnitude of the response is small. More precisely, ROA decreases only by 0.21 percentage points in the first period after a NPL shock. After, the response remains slightly below the zero line for the whole examined period.

A shock to ROA causes an immediate decrease in the NPL ratio. The NPL ratio decreases by 0.49 percentage points in the first period after a shock. Then, it reaches a low point in the second period after the shock. After that, it starts slowly rising towards to zero line. The negative effect of ROA shock on the NPL ratio is in line with the results of Anastasiou et al. (2016b).

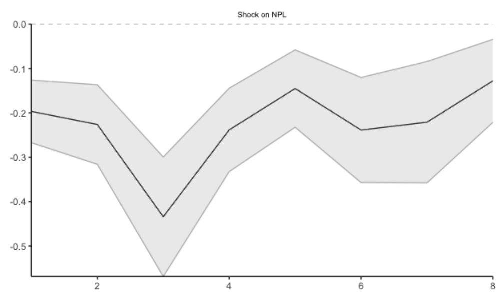
5.2.2 Core and Periphery Countries

To detect whether core countries and periphery countries react differently to shocks to NPL and their determinants, the original dataset was split into two subsamples (core and periphery) based on the location of the observation (bank). Then as in the previous section, models were estimated using the panel VAR approach. During a model selection process, we have selected models with macroeconomic determinants for the estimation.

For both models, the lag selection procedure was performed. The MMSC BIC and the MMSC HQIC for the core model suggest to use one lag in the model as the value of those criteria is the lowest one. For the periphery model, the MMSC BIC suggests to use one lag, the MMSC HQIC suggests to use two lags, and the MMSC AIC suggests to use four lags in our models. We have decided to include one lag in both models. According to the Hansen overidentification test, both models with one lag fulfill the assumption of exogenous instruments. Additionally, both models also satisfy the stability condition. The results can be seen in Appendix C.

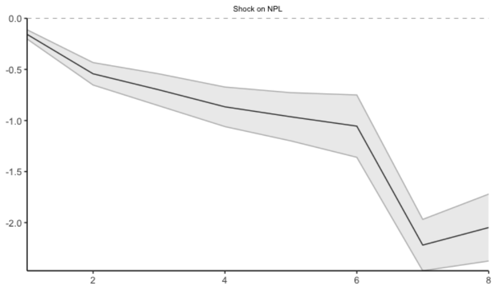
For both models, GIRF were estimated. For the confidence bands, 95% confidence intervals were estimated. The estimated GIRF suffers from a wide confidence interval. Therefore, we estimated also impulse response functions using the local projections (LP) method introduced by Jordà (2005) as a robustness check to our results. We also used 95% confidence bands for IRF estimated using the LP method. Full results of estimated GIRF and IRF using the method of local projections can be found in Appendix C and Appendix D, respetively. The overall effect shown by GIRF and IRF estimated by LP is very similar for most cases.

Figure 5.8: Impulse response function by local projections - shock to GDP growth, response of NPL ratio (Core)



Note: The grey area indicates the 95% confidence interval.

Figure 5.9: Impulse response function by local projections - shock to GDP growth, response of NPL ratio (Periphery)



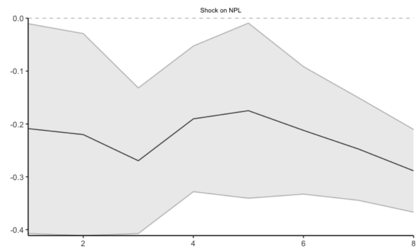
Note: The grey area indicates the 95% confidence interval.

The responses captured by GIRF between the NPL ratio and GDP growth suggest that the trajectory is very similar for both models. However, the magnitude of the effect differs. In the core model, the response of GDP growth to the NPL ratio peaks in the second period after a shock. By magnitude, the GDP ratio increases by 0.19 percentage points. Moreover, the response of the NPL ratio reaches a low point of -0.58 percentage point in the second period after a shock. In the periphery model, the response peaks in the third period after a shock. However, the GDP growth increases by 0.74 percentage points. Furthermore, the shock to GDP growth decreases the NPL ratio by 2.11 percentage points in the third period. Therefore, GIRF show that there is a larger reaction to shocks in periphery countries. The disparity in magnitudes is also captured by IRF estimated using the LP method in Figures 5.8 and 5.9.

Similar results can also be seen in GIRF capturing the unemployment rate and the NPL ratio. There is an immediate increase in the unemployment rate after a positive shock to the NPL ratio, followed by a moderate decrease. However, the magnitude of the response is bigger in periphery countries. Moreover, an increase in the unemployment rate causes an immediate growth in the NPL ratio. And again, the response is more extensive in the periphery model. More precisely, the NPL increases by 0.47 percentage points in the core model and 1.21 percentage points in the periphery model.

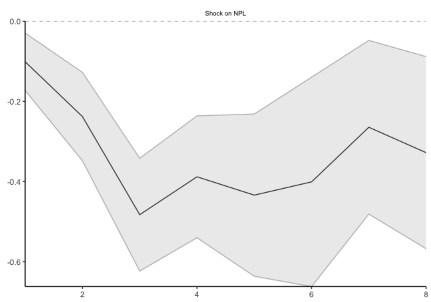
The estimated GIRF suggest that the NPL ratio in core and periphery countries does not react similarly to a positive shock to the current account balance and vice versa. In the core model, GIRF suggest that a positive NPL shock decreases the current account balance. Moreover, the response of the current account balance to the NPL ratio shock is positive. For the periphery model, the response is the opposite for both shocks.

Figure 5.10: Impulse response function by local projections - shock to government deficit, response of the NPL ratio (core)



Note: The grey area indicates 95% confidence interval.

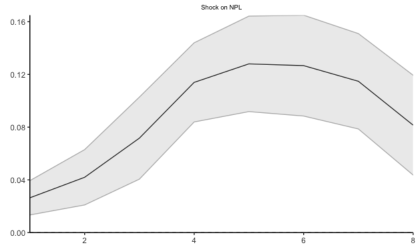
Figure 5.11: Impulse response function by local projections - shock to government deficit, response of the NPL ratio (periphery)



Note: The grey area indicates 95% confidence interval.

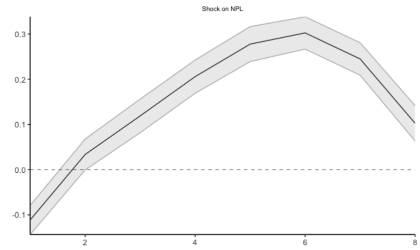
The government deficit and the NPL ratio have a similar trajectory of the responses according to estimated GIRF. In the core model, a shock to the NPL ratio decreases the government deficit immediately. After that, the response increases, reaches a peak in the third period after shock and then converges slowly to zero. Moreover, the government deficit shock causes an immediate decrease in the NPL ratio. The response reaches a low point in the second period after a shock. Then, it slowly converges to zero. The response in the periphery model is similar. However, the magnitude of the responses is much higher. Figures 5.10 and 5.11 show IRF estimated using the LP method which give the similar responses as estimated GIRF.

Figure 5.12: Impulse response function by local projections - shock to VSTOXX, response of the NPL ratio (core)



Note: The grey area indicates 95% confidence interval.

Figure 5.13: Impulse response function by local projections - shock to VSTOXX, response of the NPL ratio (periphery)



Note: The grey area indicates 95% confidence interval.

A trajectory of responses of risk aversion to a shock in the NPL ratio is not very similar for the core and periphery models. However, both responses decline at the end of the examined period. As opposed to this, the reaction to a shock in risk aversion shows the same trajectory for the core and periphery models. In addition to that, as with the previous results, the magnitude of the effects is higher in the periphery model. IRF estimated using the LP approach show the same results in Figures 5.12 and 5.13.

Chapter 6

Conclusion

In this thesis, we focused on the long-run feedback effects between NPL and their determinants in the EMU countries. It is crucial to understand the relationship between NPL and the real economy as NPL are important during a banking crisis. During the global financial crisis, the level of NPL increased rapidly in Europe. The high level of NPL signalizes the distortion of financial stability; therefore, it is crucial to understand how NPL react to shocks in their determinants and vice versa for the improvement of credit policies.

NPL are influenced by two groups of determinants - bank-specific and macroeconomic determinants. In our analysis, we use both groups of determinants to investigate feedback effects. We use return on assets and loan to deposit ratio as bank-specific determinants. Moreover, GDP growth, the government deficit, the unemployment rate, the current account balance and risk aversion were included as macroeconomic factors influencing NPL. For revealing the feedback effect between NPL and their determinants, a panel VAR approach was used as this method allows us to estimate generalized impulse response functions for exploring the reaction of variables to exposed shock. As a robustness check, we estimated two other models, which include bank-specific and macroeconomic determinants separately.

We estimated a panel VAR model on a dataset consisted of bank-specific and macroeconomic data for 17 out of 19 countries from the EMU countries over a period from 2004 to 2020. Following to this, generalized responses functions were estimated to detect a long-run response of NPL to shock in their determinants and vice versa.

Our results revealed a bi-directional relationship between non-performing loans and their determinants. Furthermore, results are supported by economic theory and other studies which examined the effects between NPL and their determinants in most cases. The results suggest that the increase in GDP growth causes a decrease in the NPL ratio. This supports a hypothesis of countercyclical behaviour of NPL. Moreover, the current account balance and the government deficit have a negative effect on the NPL ratio. On the contrary, a rise in the unemployment rate causes a worsened NPL ratio. Moreover, the increase in risk aversion and loan to deposit ratio also leads to an increase in the NPL ratio. Furthermore, a positive shock to ROA leads to a decrease in the NPL ratio.

We also revealed the effect of NPL on their determinants. The results suggest that the increase in NPL ratio leads to an increase in GDP growth followed by a decrease. Moreover, the NPL shock positively affects the current account balance. Similarly, a response of the government deficit is also positive to a NPL shock. On the contrary, a shock to NPL ratio decreases ROA and the unemployment rate.

On top of that, we aimed to reveal whether there is evidence of financial fragmentation in EMU countries. For this, we divided the original dataset into subsets based on the location of the bank. The GIRF and IRF estimated by the method of local projections suggest that the trajectory of the responses to shock is similar for core and periphery countries in most cases. However, the magnitude of the effect is much higher in periphery countries.

In conclusion, we examined a bi-directional relationship between NPL and their determinants. Moreover, we found evidence of financial fragmentation in the euro area. Our results can help policymakers to better understand the linkage between NPL and the real economy. For further research, we suggest to perform analysis with more frequent data.

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Appendix A

Panel VAR estimation

Stability Test

Figure A.1: Stability test - Full model

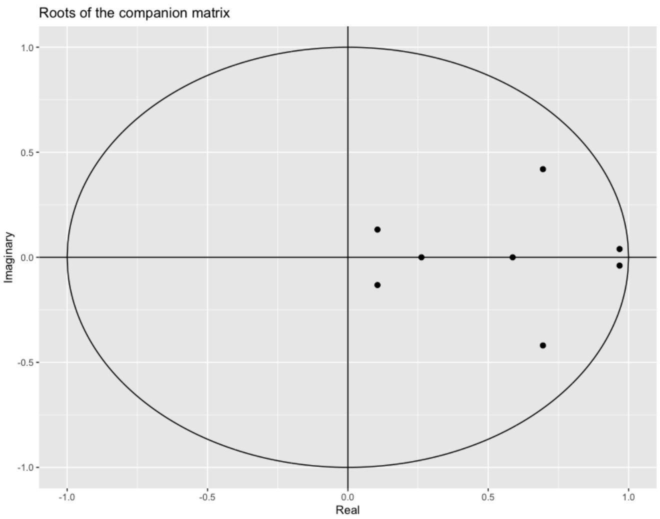


Table A.1: Results of Stability test (Full model)

Eigenvalue	Modulus
0.9679253+0.0394292i	0.96872802
0.9679253-0.0394292i	0.96872803
0.6949746+0.4196483i	0.81184624
0.6949746-0.4196483i	0.81184625
0.5871376+0.0000000i	0.58713766
0.2621366+0.0000000i	0.26213667
0.1055182+0.1320244i	0.16901048
0.1055182-0.1320244i	0.1690104

Figure A.2: Stability test - Bank model

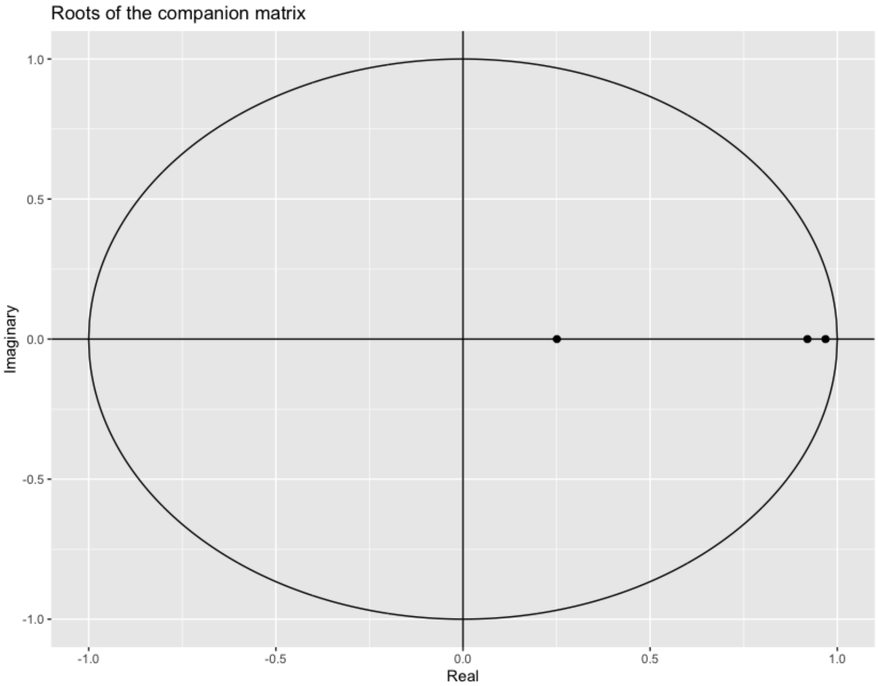


Table A.2: Results of Stability test (Bank model)

Eigenvalue	Modulus
0.9686798	0.9686798
0.9202784	0.9202784
0.2508846	0.2508846

Figure A.3: Stability test - Macro model

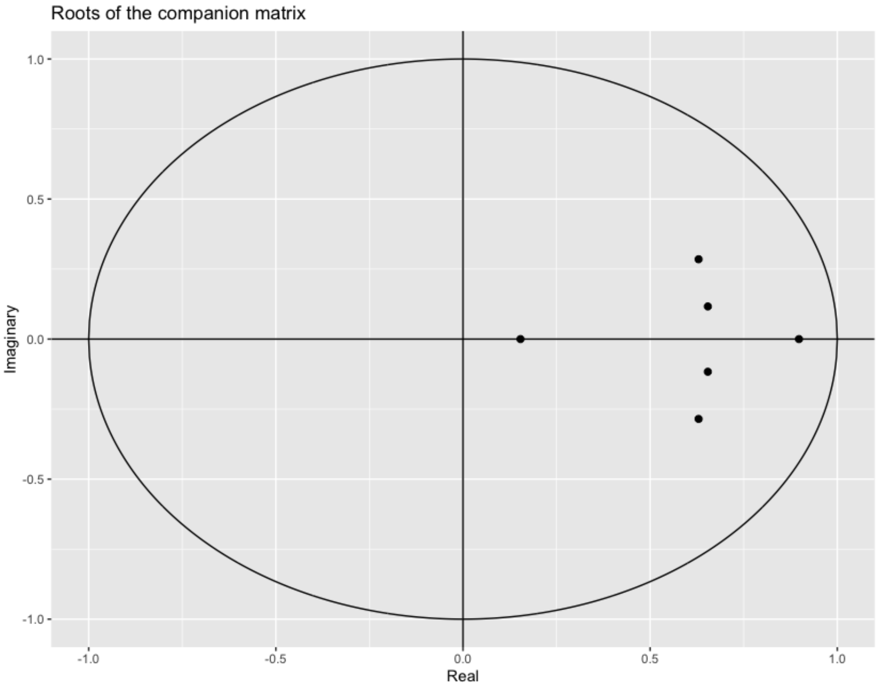


Table A.3: Results of Stability test (Macro model)

Eigenvalue	Modulus
0.8977007+0.0000000i	0.89770072
0.6295118+0.2850616i	0.69104653
0.6295118-0.2850616i	0.69104654
0.6541773+0.1166043i	0.66448815
0.6541773-0.1166043i	0.66448816
0.1535824+0.0000000i	0.1535824

Panel VAR estimation

Table A.4: Results of Panel VAR model (Bank model)

Dynamic Panel VAR estimation, two-step GMM			
Transformation: Forward orthogonal deviations			
Group variable: Bank name			
Time variable: Year			
	NPL	ROA	LTD
NPL_l11	0.9427***	−0.0186	0.5812***
	(0.0679)	(0.0207)	(0.1730)
ROA_l11	−0.7305**	0.2755***	−0.0814
	(0.2324)	(0.0513)	(0.5751)
LTD_l1	0.0069	0.0060	0.9216***
	(0.0095)	(0.0043)	(0.0354)

*p<0.5; **p<0.01; ***p<0.001

Hansen test of overid. restrictions:
chi2(135) = 101.46 Prob > chi2 = 0.986

Note: LTD = loan to deposit ratio

Table A.5: Results of Panel VAR model (Macro model)

Dynamic Panel VAR estimation, two-step GMM

Transformation: Forward orthogonal deviations

Group variable: Bank name

Time variable: Year

	NPL	GDPg	GDEF	UN	CAB	VSTOXX
NPL_l1	0.9236***	0.2337***	0.2118***	−0.0715**	0.1640**	−0.6116***
	(0.0504)	(0.0651)	(0.0506)	(0.0230)	(0.0633)	(0.1008)
GDPg_l1	−0.3138***	0.3885***	0.1410	−0.2132***	−0.1531*	0.9774***
	(0.0606)	(0.1131)	(0.0776)	(0.0550)	(0.0613)	(0.0930)
GDEF_ l1	−0.0292	0.1435	0.5144***	−0.1981***	0.1797**	−0.0384
	(0.0665)	(0.0763)	(0.0723)	(0.0492)	(0.0636)	(0.1236)
UN_l1	0.1662**	0.2189*	0.0324	0.8799***	0.1284*	0.7983***
	(0.0638)	(0.0872)	(0.0792)	(0.0385)	(0.0630)	(0.1509)
CAB_l1	−0.2223***	−0.4254***	−0.1725	−0.0326	0.2982**	−0.2050
	(0.0646)	(0.0981)	(0.1090)	(0.0340)	(0.0975)	(0.1451)
VSTOXX_l1	−0.0161	−0.0029	−0.0549**	0.0095	−0.0183	0.6140***
	(0.0205)	(0.0289)	(0.0207)	(0.0112)	(0.0215)	(0.0386)

*p<0.5; **p<0.01; ***p<0.001

Hansen test of overid. restrictions:

chi2(180) = 155.57 Prob > chi2 = 0.906

Note: GDPg= GDP growth; GDEF = government deficit; UN=unemployment rate; CAB = current account balance.

Table A.6: Results of Panel VAR model (Full model)

Dynamic Panel VAR estimation, two-step GMM

Transformation: Forward orthogonal deviations

Group variable: Bank name

Time variable: Year

	NPL	ROA	LTD	GDPg	GDEF	UN	CAB	VSTOXX
NPL_l1	0.9341***	−0.0426	−0.1816	0.2130*	0.2166**	−0.1274***	0.0929	−0.4134***
	(0.0640)	(0.0377)	(0.1715)	(0.0922)	(0.0700)	(0.0339)	(0.0617)	(0.1215)
ROA_l1	−0.3711	0.2594	0.5465	0.2989	0.0563	−0.3111*	−0.2430	0.5912*
	(0.2716)	(0.1909)	(0.4685)	(0.2005)	(0.2083)	(0.1517)	(0.1872)	(0.2672)
LTD_l1	0.0007	−0.0037	0.8878***	−0.0305**	−0.0407***	0.0055	0.0173**	0.1683***
	(0.0071)	(0.0034)	(0.0367)	(0.0107)	(0.0089)	(0.0051)	(0.0064)	(0.0164)
GDPg_l1	−0.2725**	0.0471	−0.1231	0.3777**	0.1506	−0.1752*	−0.0886	0.692***
	(0.0964)	(0.0769)	(0.2731)	(0.1275)	(0.0888)	(0.0724)	(0.0758)	(0.1311)
GDEF_l1	−0.0549	0.0402	0.2441	0.1208	0.5122***	−0.1659**	0.2822***	−0.5788***
	(0.0936)	(0.0636)	(0.2711)	(0.0944)	(0.0871)	(0.0578)	(0.0781)	(0.1600)
UN_l1	0.0919	0.0280	0.7808*	0.3726***	0.1778*	0.8931***	0.0765	−0.2245
	(0.0858)	(0.0380)	(0.3949)	(0.0993)	(0.0694)	(0.0397)	(0.0630)	(0.1680)
CAB_l1	−0.1529*	0.0714	−0.2933	−0.3721***	−0.0606	−0.0311	0.2874***	−0.2812*
	(0.0753)	(0.0506)	(0.2861)	(0.1032)	(0.1071)	(0.0641)	(0.0796)	(0.1340)
VSTOXX_l1	−0.0046	0.0145	0.2539	0.0399	0.0329	0.0064	−0.0357	0.2344***
	(0.0267)	(0.0134)	(0.1373)	(0.0311)	(0.0245)	(0.0168)	(0.0239)	(0.0488)

*p<0.5; **p<0.01; ***p<0.001

Hansen test of overid. restrictions:

chi2(192) = 136.57 Prob > chi2 = 0.999

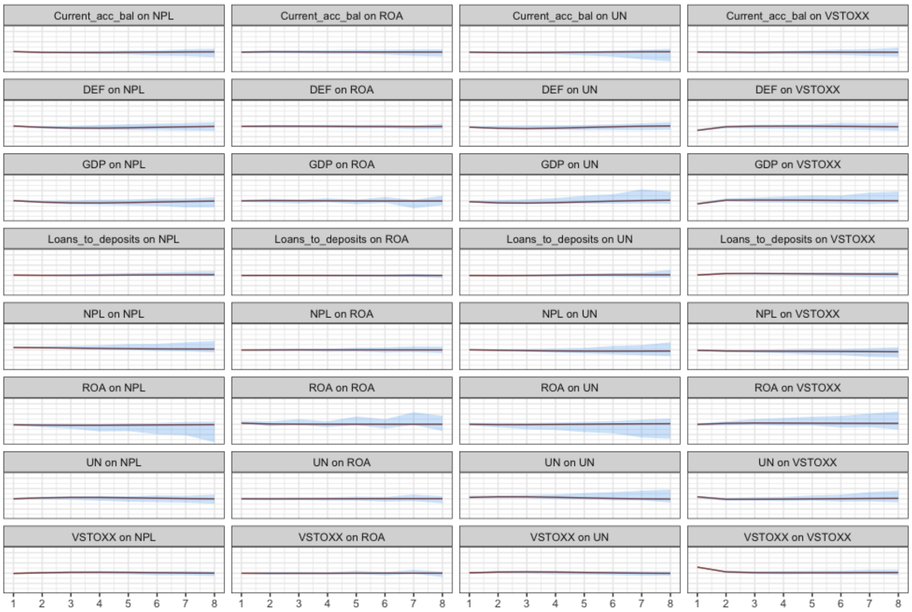
Note: GDPg= GDP growth; GDEF = government deficit; UN=unemployment rate; CAB = current account balance; LTD=loan to deposit.

Appendix B

Generalized Impulse Response Functions

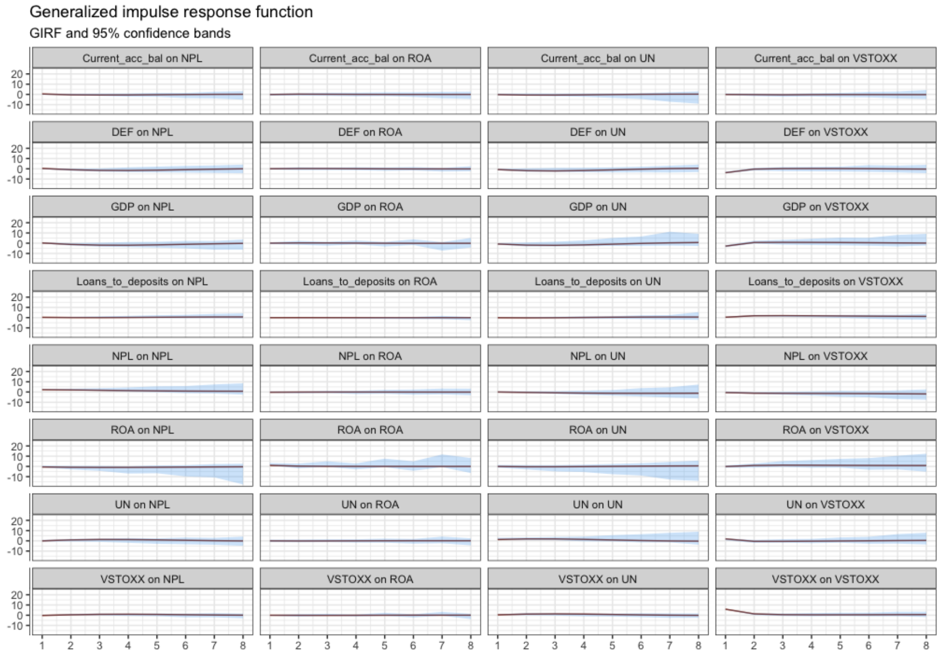
Full model

Figure B.1: Generalized impulse response functions - Full model (all variables) - part 1



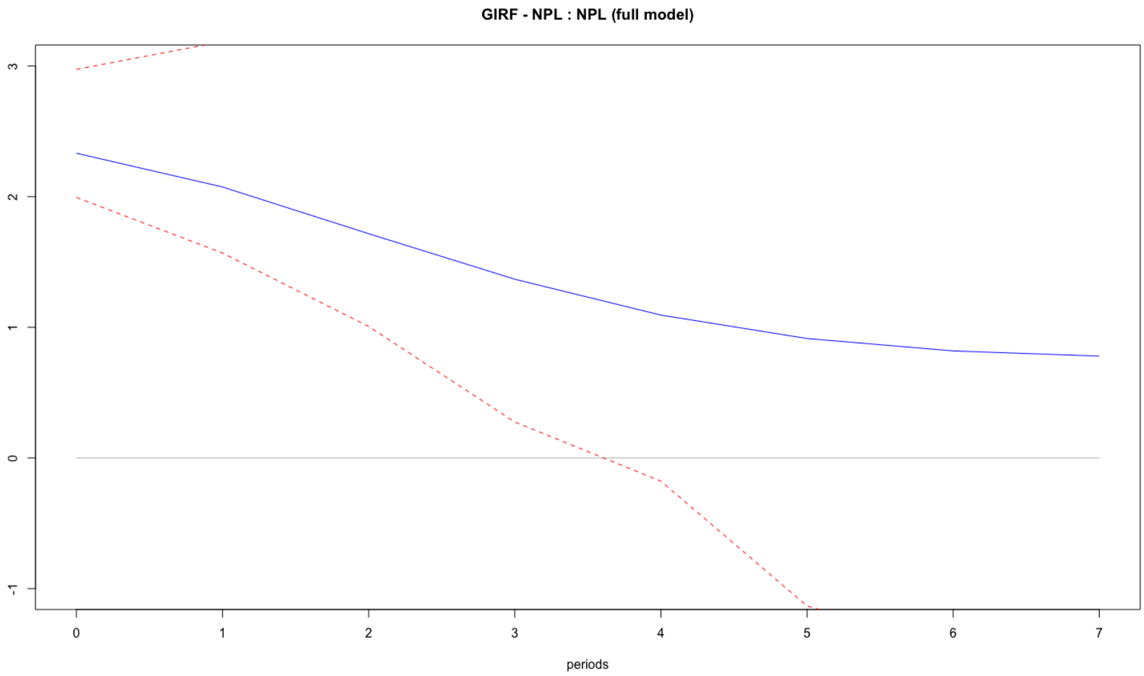
Note: Shock is imposed in Period 1.

Figure B.2: Generalized impulse response functions - Full model (all variables) - part 2



Note: Shock is imposed in Period 1.

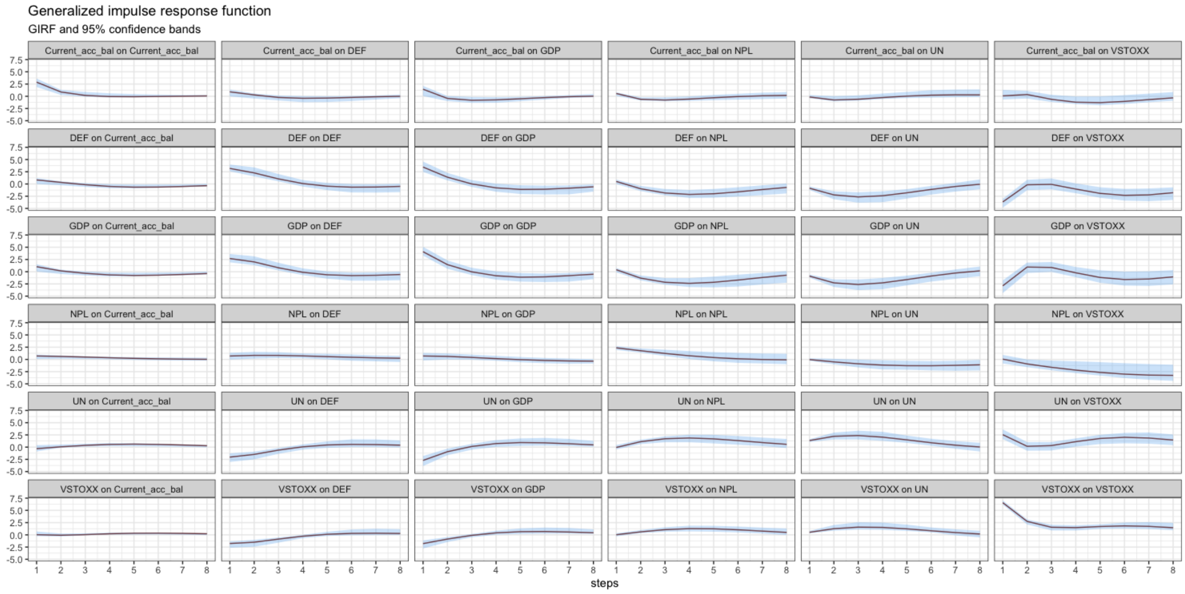
Figure B.3: Generalized impulse response functions - shock to NPL ratio response of the NPL ratio



Note: The dashed lines indicate 95% confidence interval.

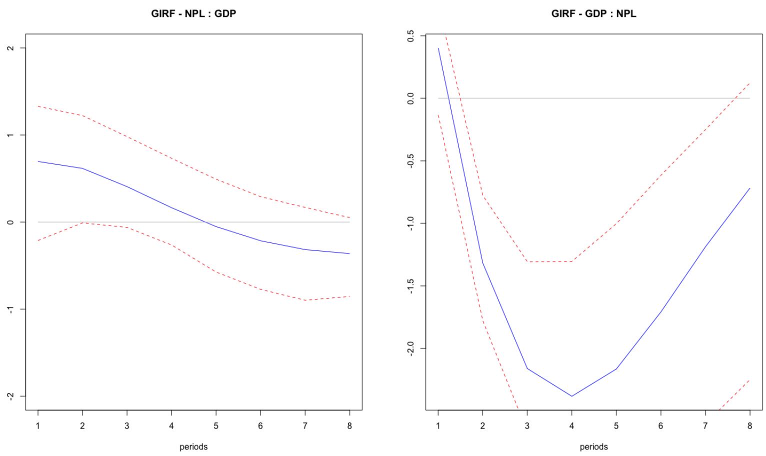
Macro model

Figure B.4: Generalized impulse response functions - Macro model (all variables)



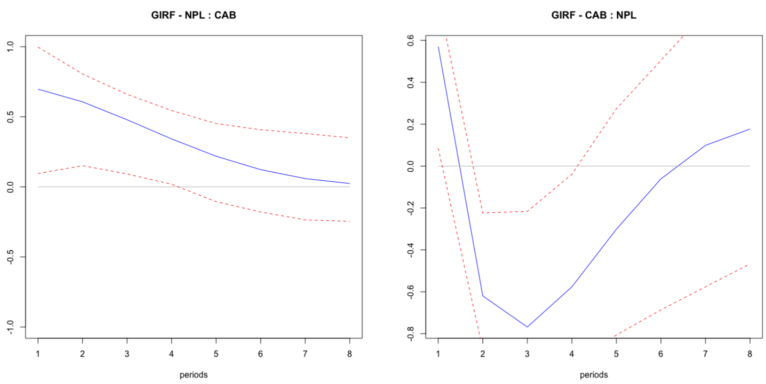
Note: Shock is imposed in Period 1.

Figure B.5: Generalized impulse response functions - Macro model
(a) Shock to NPL ratio response of GDP growth (left)
(b) Shock to GDP growth, response of the NPL ratio (right)



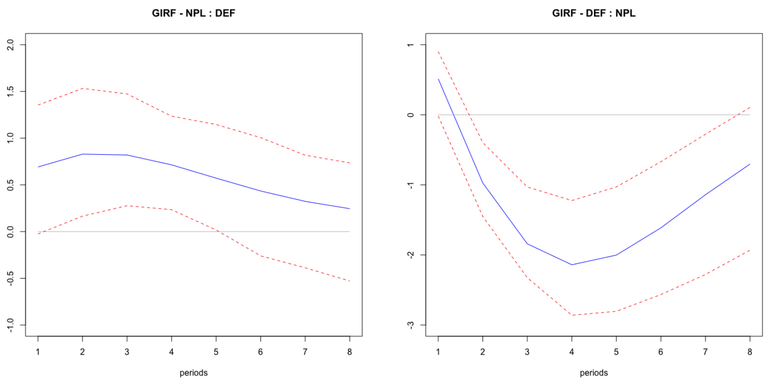
Note: The dashed lines indicate 95% confidence interval.

Figure B.6: Generalized impulse response functions - Macro model
(a) Shock to NPL ratio response of current account balance (left)
(b) Shock to current account balance, response of the NPL ratio (right)



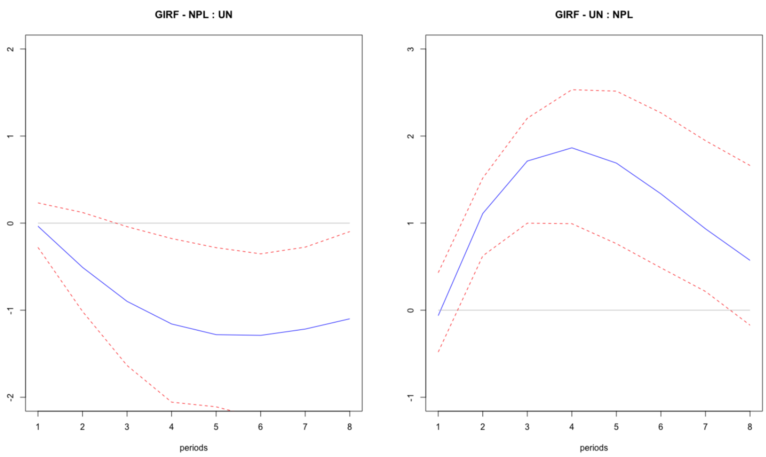
Note: The dashed lines indicate 95% confidence interval.

Figure B.7: Generalized impulse response functions - Macro model
(a) Shock to NPL ratio response of government deficit (left)
(b) Shock to government deficit, response of the NPL ratio (right)



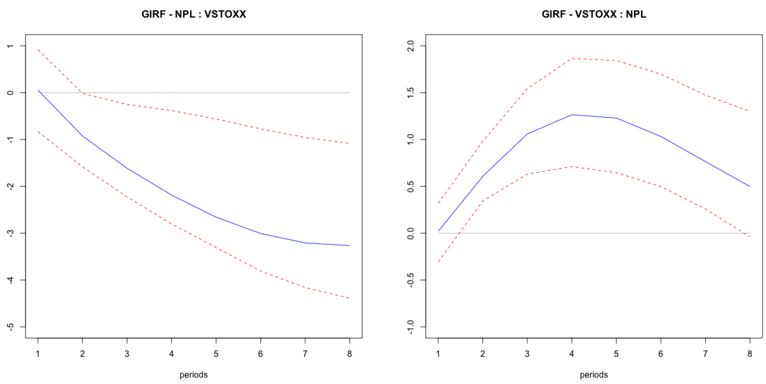
Note: The dashed lines indicate 95% confidence interval.

Figure B.8: Generalized impulse response functions - Macro model
(a) Shock to NPL ratio response of unemployment rate (left)
(b) Shock to unemployment rate, response of the NPL ratio (right)



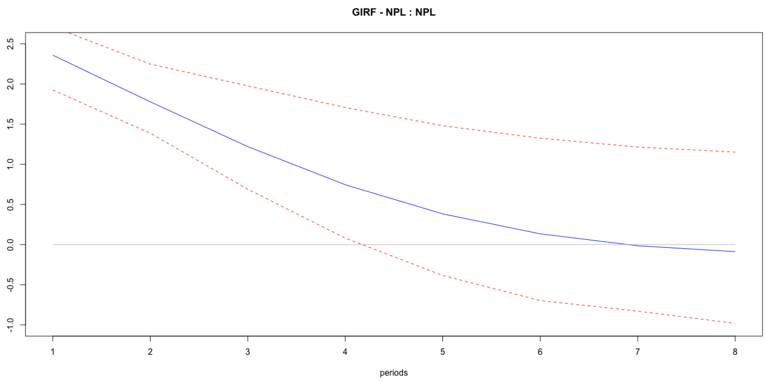
Note: The dashed lines indicate 95% confidence interval.

Figure B.9: Generalized impulse response functions - Macro model
(a) Shock to NPL ratio response of VSTOXX (left)
(b) Shock to VSTOXX, response of the NPL ratio (right)



Note: The dashed lines indicate 95% confidence interval.

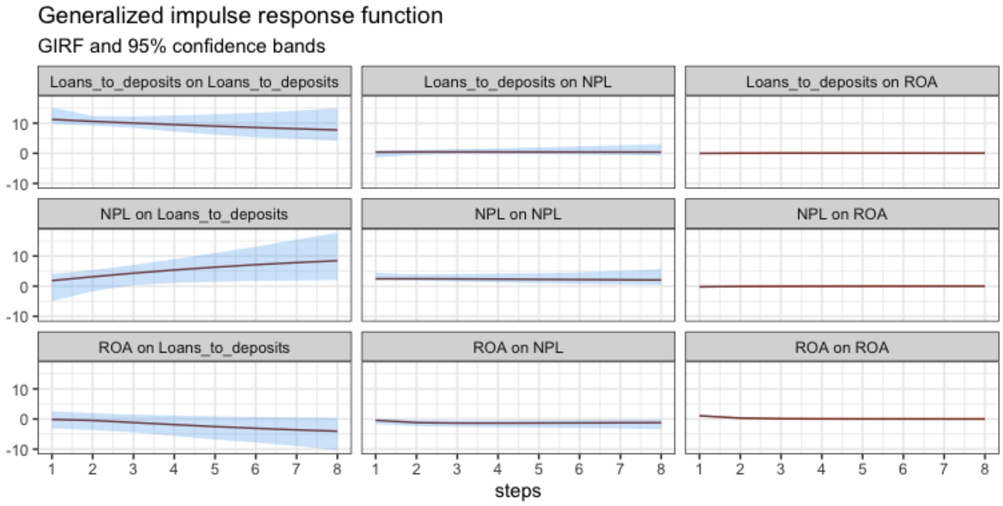
Figure B.10: Generalized impulse response functions - Macro model
- shock to NPL ratio response of NPL ratio



Note: The dashed lines indicate 95% confidence interval.

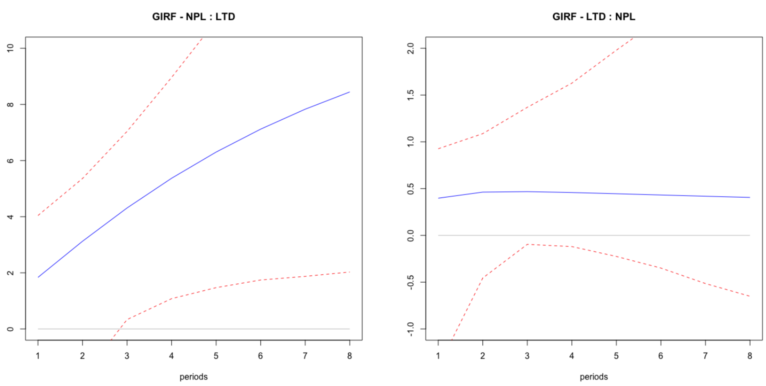
Bank model

Figure B.11: Generalized impulse response functions - Bank model (all variables)



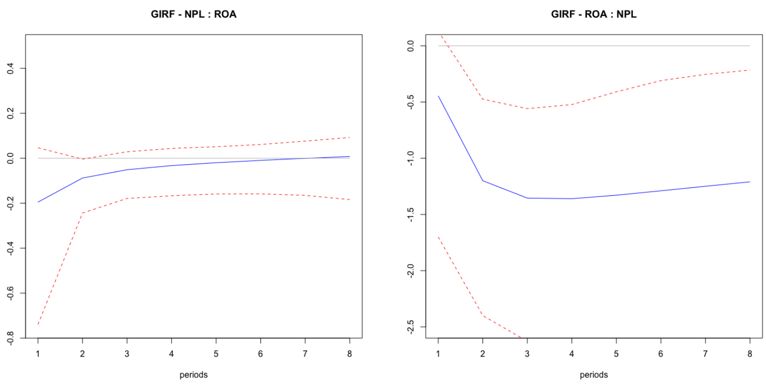
Note: Shock is imposed in Period 1.

Figure B.12: Generalized impulse response functions - Bank model (a) Shock to NPL ratio response of loan to deposit (left) (b) Shock to loan to deposit, response of the NPL ratio (right)



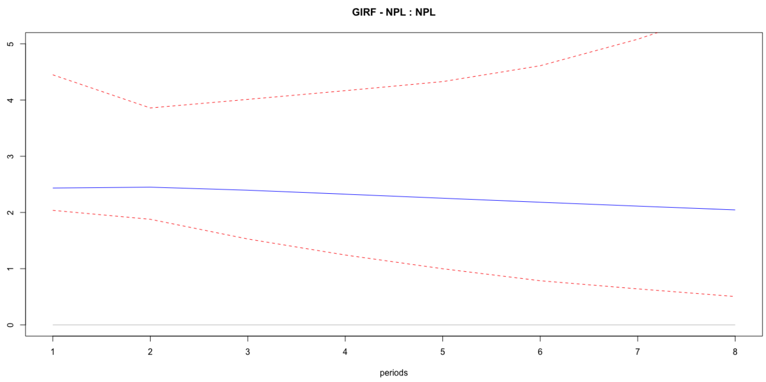
Note: The dashed lines indicate 95% confidence interval.

Figure B.13: Generalized impulse response functions - Bank model
(a) Shock to NPL ratio response of ROA (left)
(b) Shock to ROA, response of the NPL ratio (right)



Note: The dashed lines indicate 95% confidence interval.

Figure B.14: Generalized impulse response functions - Bank model - shock to NPL ratio response of NPL ratio



Note: The dashed lines indicate 95% confidence interval.

Appendix C

Financial fragmentation

Lag selection

Table C.1: Lag length selection (Core and Periphery model)

Model	Lag number	MMSC BIC	MMSC AIC	MMSC HQIC
Core model	1	**-780.3735**	-200.1446	**-453.1119**
Core model	2	-732.9219	-203.7585	-436.8411
Core model	3	-659.3031	-179.4772	-392.9776
Core model	4	-669.4622	**-239.8946**	-433.118
Periphery model	1	**-782.377**	-204.9645	-456.977
Periphery model	2	-752.8359	-224.9763	**-457.6029**
Periphery model	3	-681.9855	-203.6823	-416.6316
Periphery model	4	-669.8119	**-239.7924**	-433.1858

Stability

Core

Figure C.1: Stability test (Core)

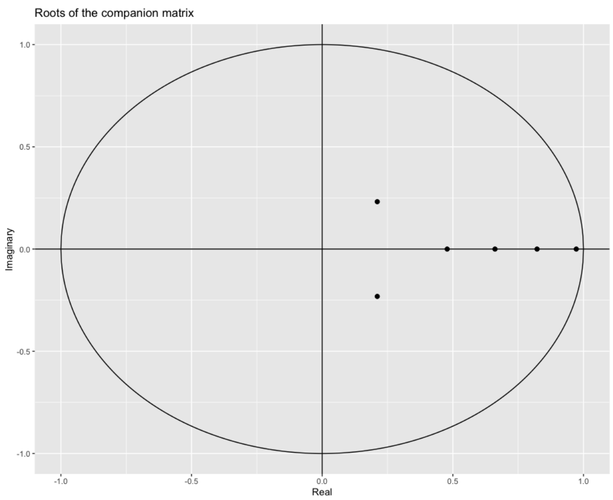


Table C.2: Results of Stability test (Core)

Eigenvalue	Modulus
0.9724062+0.0000000i	0.97240622
0.8222885+0.0000000i	0.82228853
0.6613255+0.0000000i	0.66132554
0.4782521+0.0000000i	0.47825215
0.2107967+0.2315825i	0.31315446
0.2107967-0.2315825i	0.3131544

Periphery

Figure C.2: Stability test (Periphery)

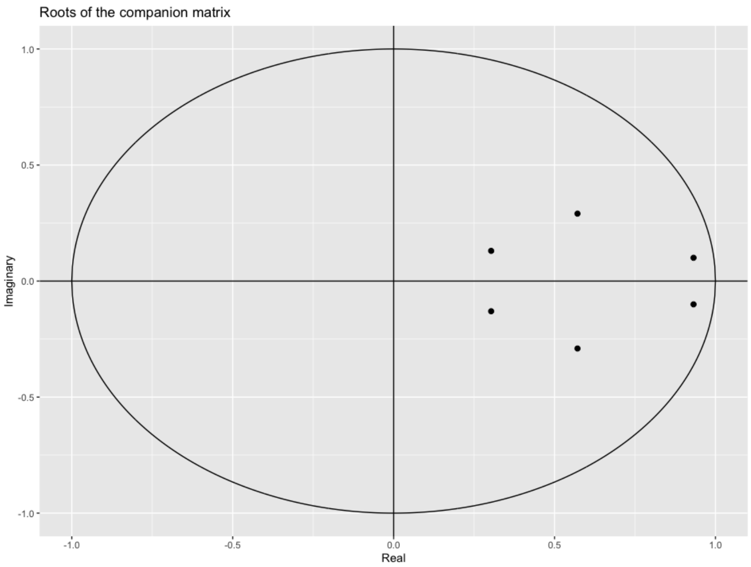


Table C.3: Results of Stability test (Periphery)

Eigenvalue	Modulus
0.9318546+0.1003000i	0.93723702
0.9318546-0.1003000i	0.93723703
0.5713092+0.2905750i	0.64095874
0.5713092-0.2905750i	0.64095875
0.3030088+0.1301096i	0.32976186
0.3030088-0.1301096i	0.3297618

Panel VAR estimation

Table C.4: Results of Panel VAR model (Periphery)

Dynamic Panel VAR estimation, two-step GMM

Transformation: Forward orthogonal deviations

Group variable: Bank name

Time variable: Year

	NPL	UN	GDP	GDEF	CAB	VSTOXX
NPL_l1	0.9830***	0.0353	0.1657	0.1409	0.2411*	−0.5579***
	(0.0672)	(0.0580)	(0.0846)	(0.0735)	(0.0992)	(0.1257)
UN_l1	0.0172	0.7882***	0.1960	0.0241	−0.1025	0.8490***
	(0.0799)	(0.0701)	(0.1185)	(0.1137)	(0.1256)	(0.1653)
GDPg_l1	−0.3091**	−0.3124*	0.4724***	0.1759	−0.2027*	0.9341***
	(0.1060)	(0.1337)	(0.1294)	(0.1194)	(0.0974)	(0.1246)
GDEF_ l1	−0.0736	−0.1051	0.0842	0.4174**	−0.0978	0.1615
	(0.1426)	(0.1234)	(0.1312)	(0.1388)	(0.1493)	(0.1535)
CAB_l1	−0.1801**	−0.0987	−0.2637**	−0.0082	0.3909*	−0.5651***
	(0.0649)	(0.0762)	(0.0952)	(0.0902)	(0.1576)	(0.1012)
VSTOXX_l1	0.0222	0.0594	−0.0676	−0.1005*	−0.1407**	0.5604***
	(0.0379)	(0.0387)	(0.0454)	(0.0450)	(0.0532)	(0.0620)

*p<0.5; **p<0.01; ***p<0.001

Hansen test of overid. restrictions:

chi2(108) = 71.04 Prob > chi2 = 0.998

Note: GDPg= GDP growth; GDEF = government deficit; UN=unemployment rate; CAB = current account balance.

Table C.5: Results of Panel VAR model (Core)

Dynamic Panel VAR estimation, two-step GMM

Transformation: Forward orthogonal deviations

Group variable: Bank name

Time variable: Year

	NPL	UN	GDP	GDEF	CAB	VSTOXX
NPL_l1	0.7944***	−0.0484	0.0722	0.0657	−0.0415	0.0914
	(0.1198)	(0.0298)	(0.0692)	(0.0622)	(0.0457)	(0.1490)
UN_l1	0.0259	0.8526***	0.3929***	0.0878	−0.1084	0.3771
	(0.1016)	(0.0435)	(0.1157)	(0.0974)	(0.0696)	(0.1937)
GDPg_l1	−0.1001	−0.0859	0.0188	0.0535	−0.0009	0.9705***
	(0.0539)	(0.0529)	(0.0841)	(0.0777)	(0.0732)	(0.1694)
GDEF_ l1	−0.0439	−0.0753	−0.3183**	0.3029***	0.0892	−0.1722
	(0.0547)	(0.0517)	(0.1125)	(0.0913)	(0.0835)	(0.1663)
CAB_l1	0.0785	0.1544*	−0.3018*	−0.2702*	0.7767***	0.8775***
	(0.0875)	(0.0671)	(0.1441)	(0.1255)	(0.0739)	(0.2571)
VSTOXX_l1	0.0154	0.0311*	−0.0640*	−0.0777**	0.0797***	0.6106***
	(0.0203)	(0.0150)	(0.0300)	(0.0279)	(0.0215)	(0.0531)

*p<0.5; **p<0.01; ***p<0.001

Hansen test of overid. restrictions:

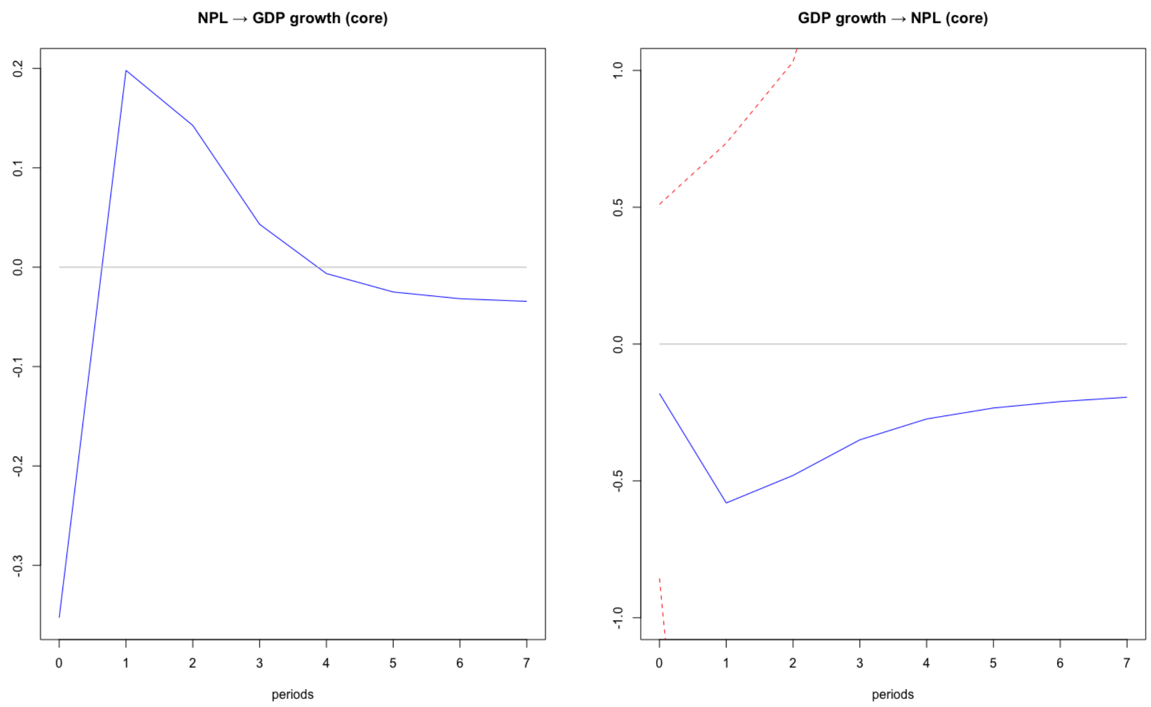
chi2(108) = 75.86 Prob > chi2 = 0.992

Note: GDPg= GDP growth; GDEF = government deficit; UN=unemployment rate; CAB = current account balance.

Generalized Impulse Response Functions

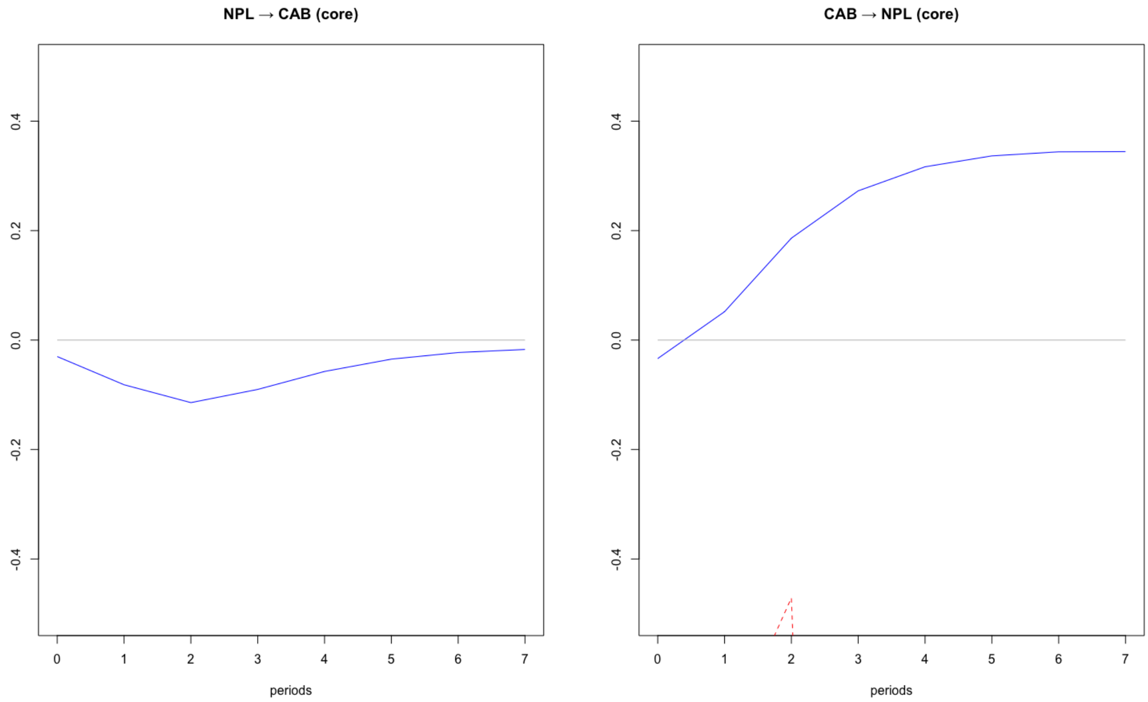
Core

Figure C.3: Generalized impulse response functions - Core model
(a) Shock to NPL ratio, response of GDP growth (left)
(b) Shock to GDP growth, response of the NPL ratio (right)



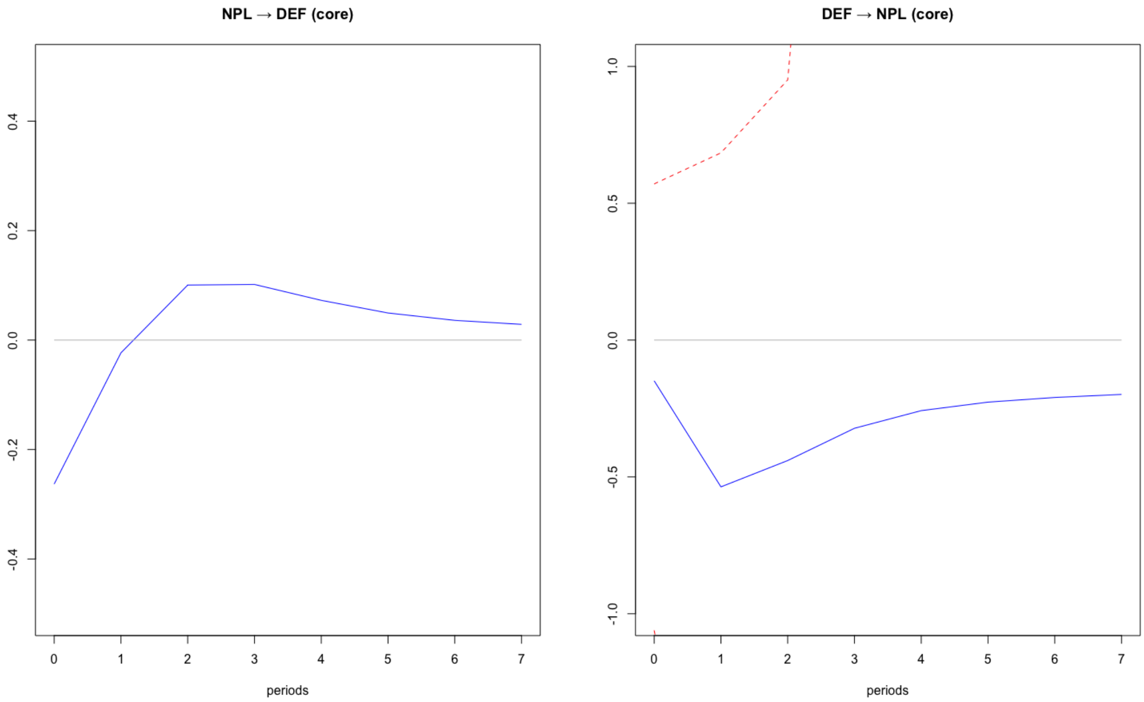
Note: The dashed line indicates 95% confidence interval.

Figure C.4: Generalized impulse response functions - Core model
(a) Shock to NPL ratio, response of current account balance (left)
(b) Shock to current account balance, response of the NPL ratio (right)



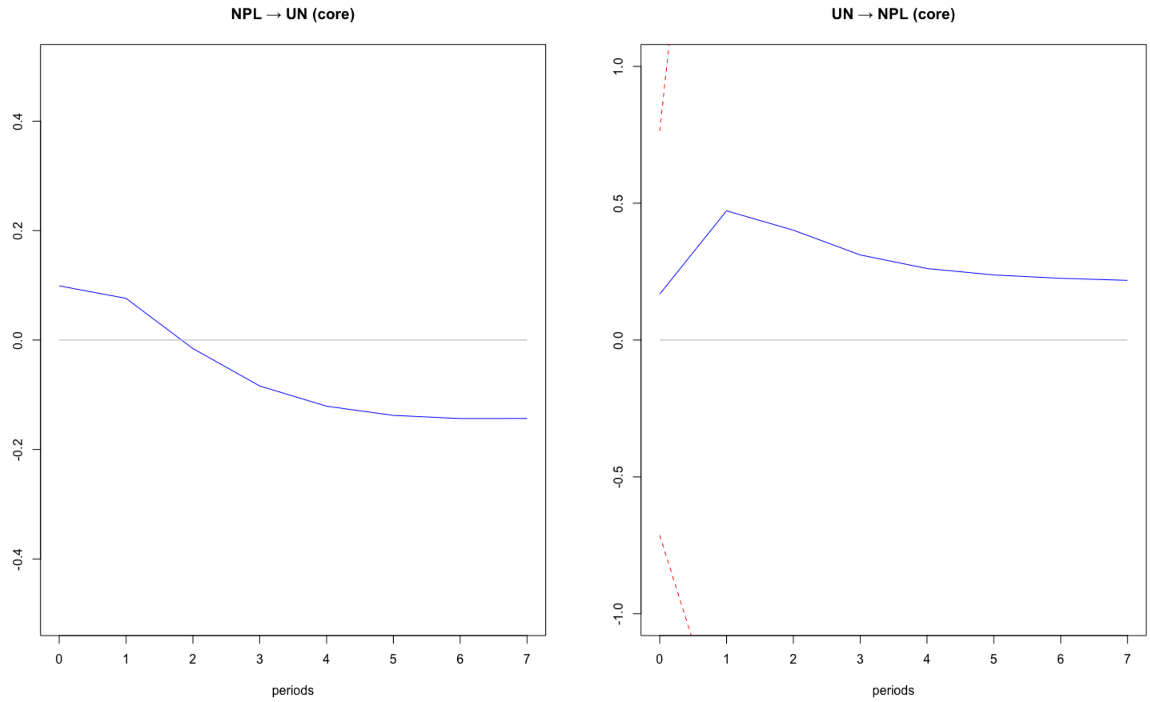
Note: The dashed line indicates 95% confidence interval.

Figure C.5: Generalized impulse response functions - Core model
(a) Shock to NPL ratio, response of government deficit (left)
(b) Shock to government deficit, response of the NPL ratio (right)



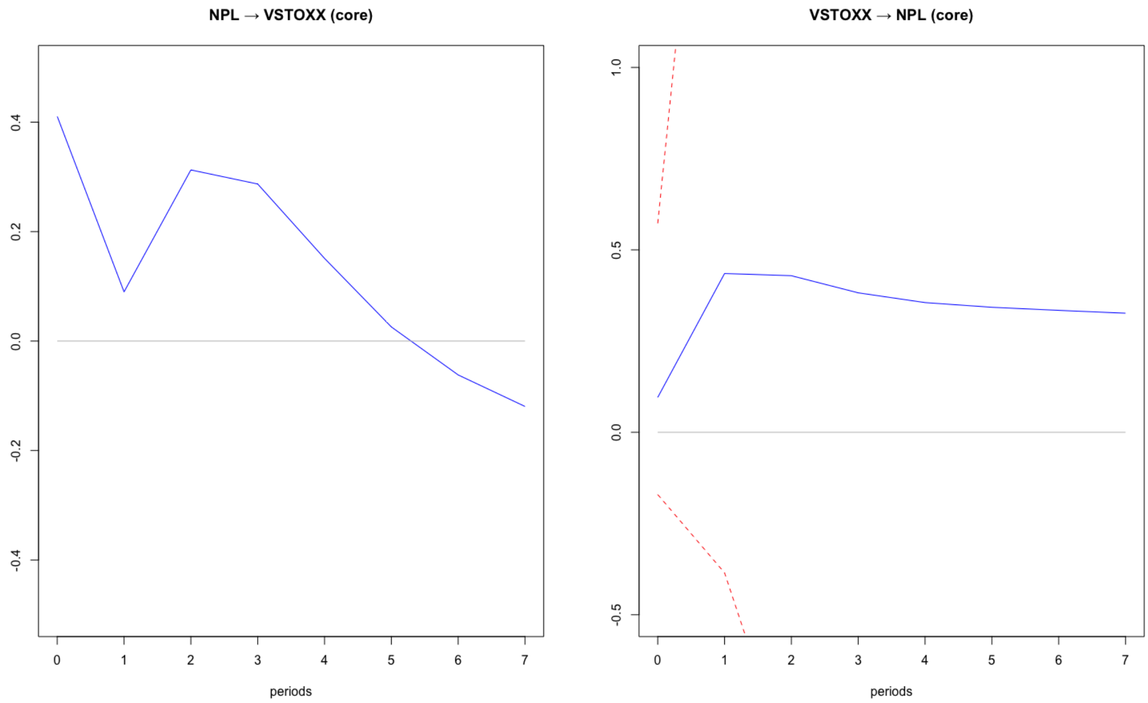
Note: The dashed line indicates 95% confidence interval.

Figure C.6: Generalized impulse response functions - Core model
(a) Shock to NPL ratio, response of unemployment rate (left)
(b) Shock to unemployment rate, response of the NPL ratio (right)



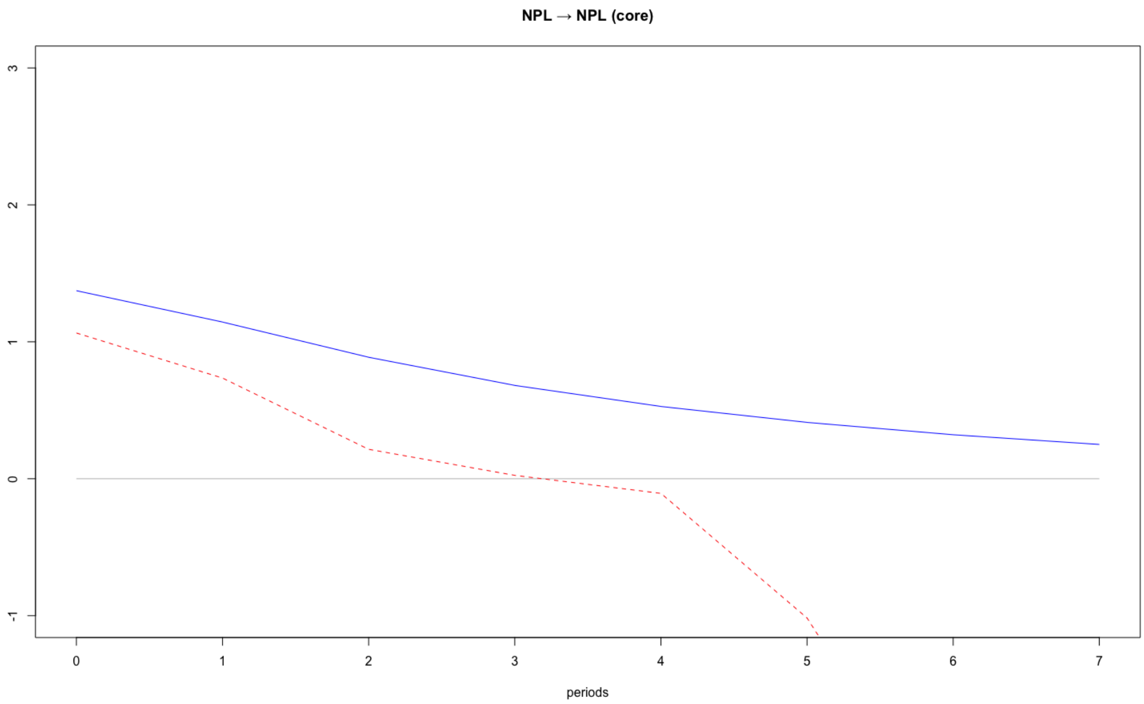
Note: The dashed line indicates 95% confidence interval.

Figure C.7: Generalized impulse response functions - Core model
(a) Shock to NPL ratio, response of VSTOXX (left)
(b) Shock to VSTOXX, response of the NPL ratio (right)



Note: The dashed line indicates 95% confidence interval.

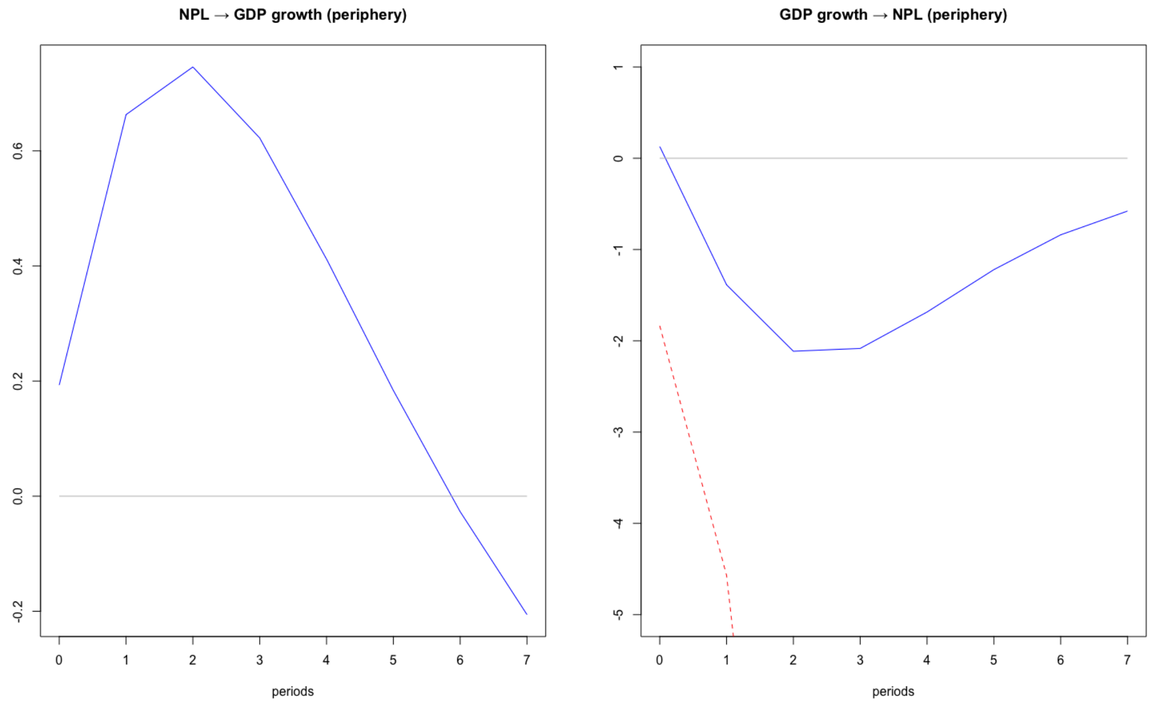
Figure C.8: Generalized impulse response functions - Core model - shock to NPL ratio, response of NPL ratio



Note: The dashed line indicates 95% confidence interval.

Periphery

Figure C.9: Generalized impulse response functions - Periphery model
(a) Shock to NPL ratio, response of GDP growth (left)
(b) Shock to GDP growth, response of the NPL ratio (right)



Note: The dashed line indicates 95% confidence interval.

Figure C.10: Generalized impulse response functions - Periphery model
(a) Shock to NPL ratio, response of current account balance (left)
(b) Shock to current account balance, response of the NPL ratio (right)

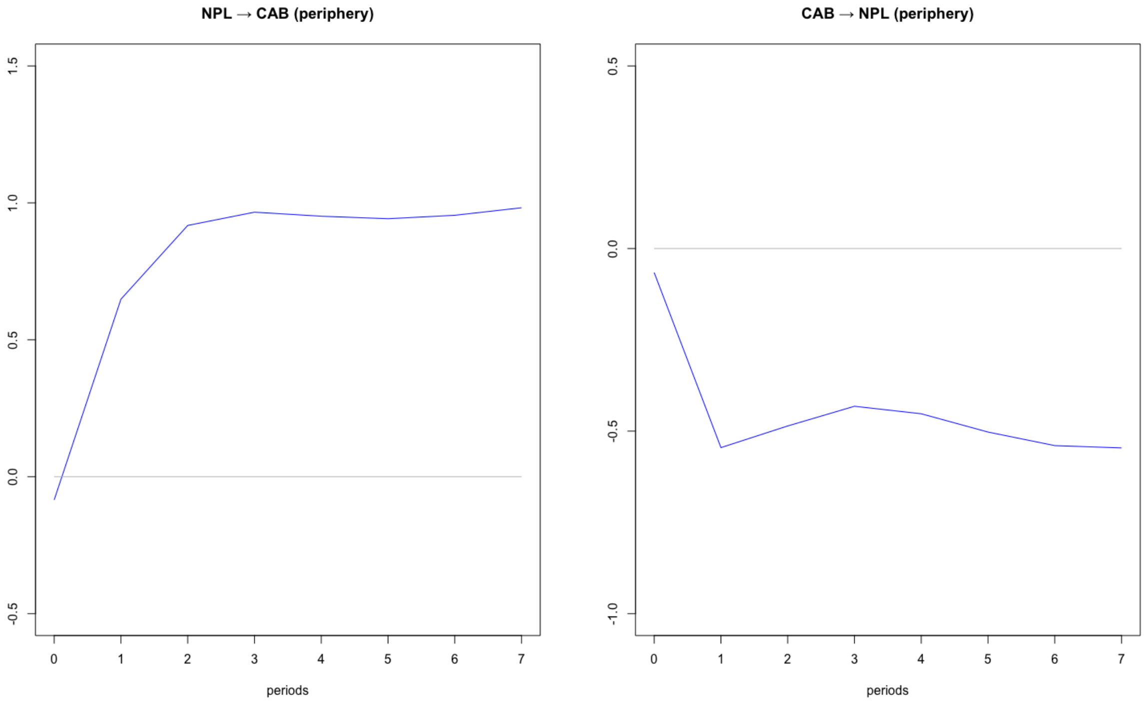
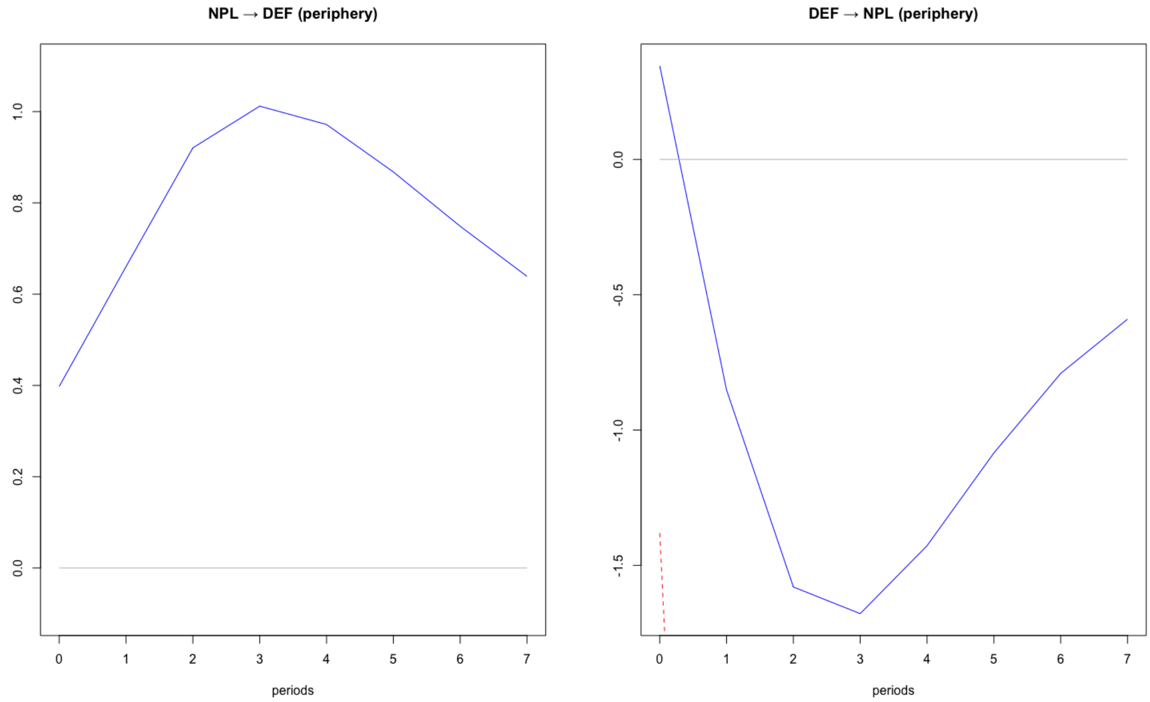


Figure C.11: Generalized impulse response functions - Periphery model
(a) Shock to NPL ratio, response of government deficit (left)
(b) Shock to government deficit, response of the NPL ratio (right)



Note: The dashed line indicates 95% confidence interval.

Figure C.12: Generalized impulse response functions - Periphery model
(a) Shock to NPL ratio, response of unemployment rate (left)
(b) Shock to unemployment rate, response of the NPL ratio (right)

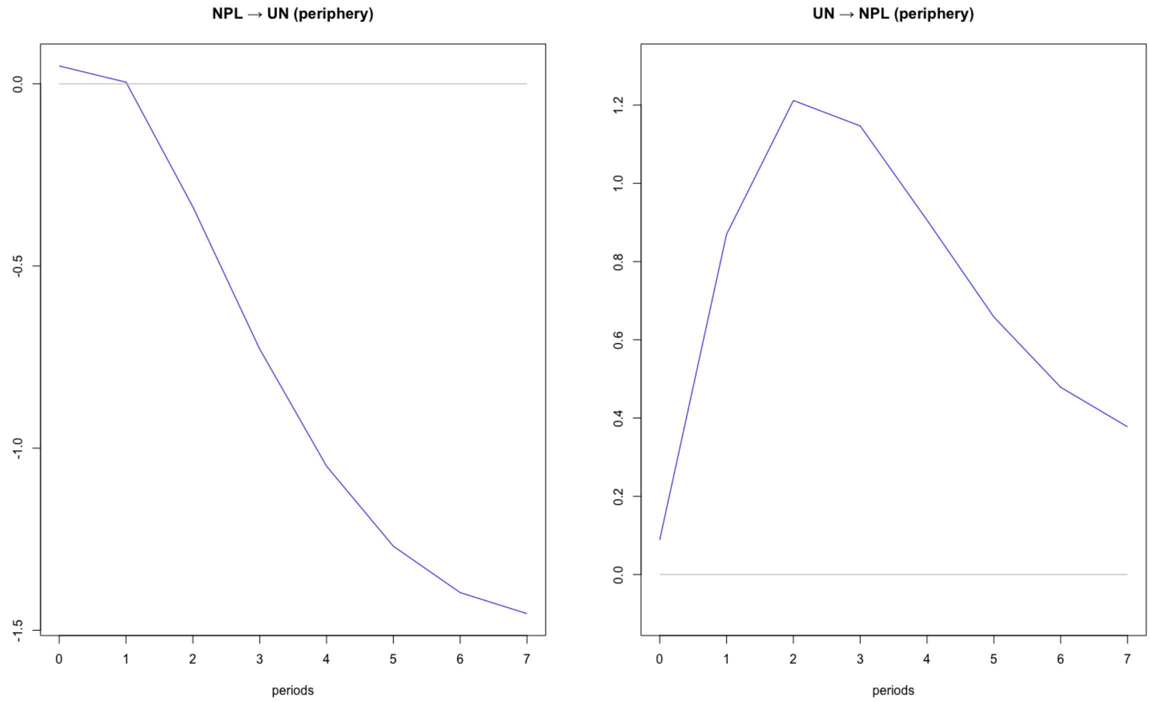
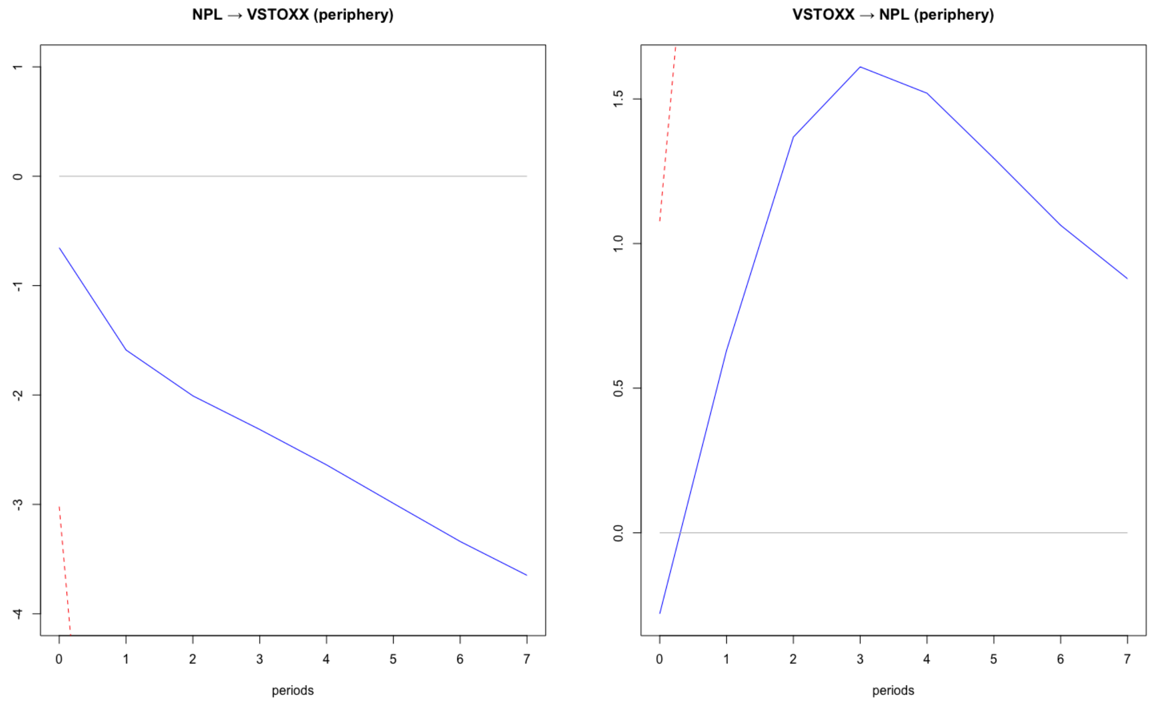
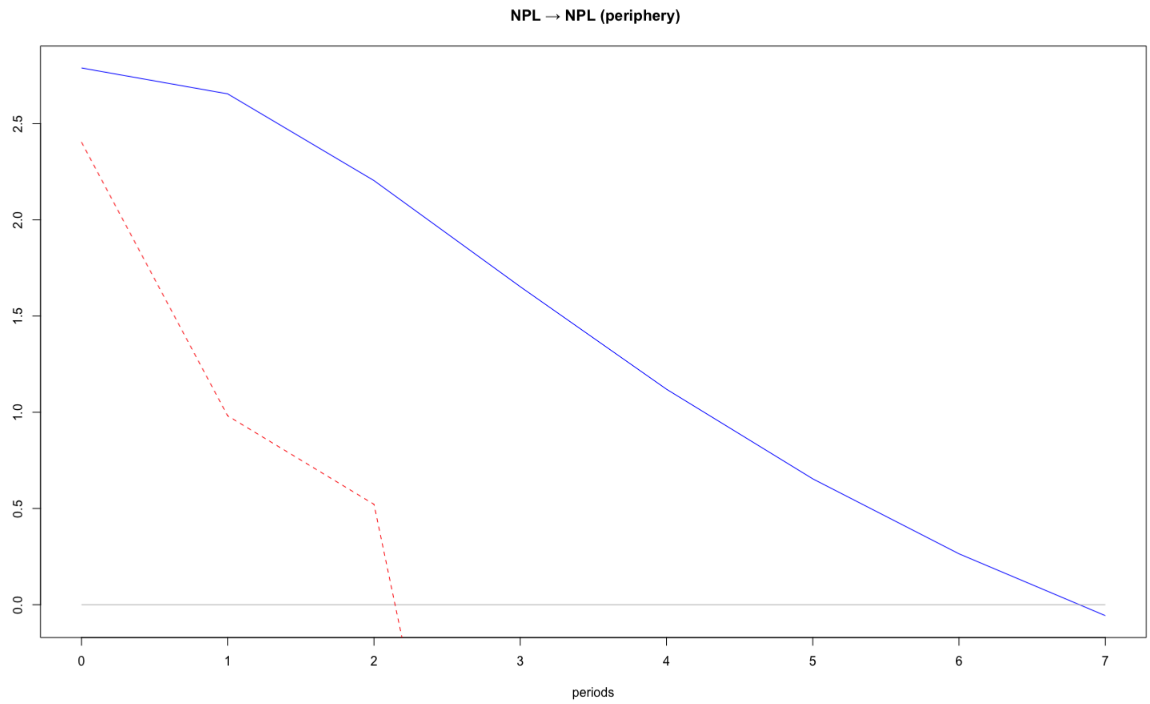


Figure C.13: Generalized impulse response functions - Periphery model
(a) Shock to NPL ratio, response of VSTOXX (left)
(b) Shock to VSTOXX, response of the NPL ratio (right)



Note: The dashed line indicates 95% confidence interval.

Figure C.14: Generalized impulse response functions - Periphery model - shock to NPL ratio response of NPL ratio



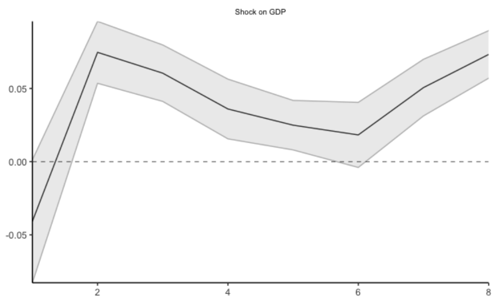
Note: The dashed line indicates 95% confidence interval.

Appendix D

Local Projections - Impulse Response Functions

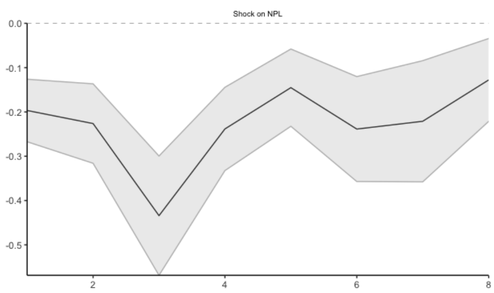
Core

Figure D.1: IRF - shock to NPL ratio, response of GDP growth (Core)



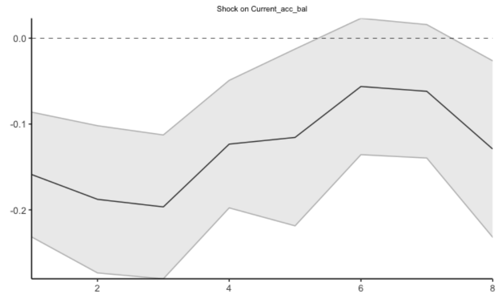
Note: The grey lines indicate 95% confidence interval.

Figure D.2: IRF - shock to GDP growth, response of NPL ratio (Core)



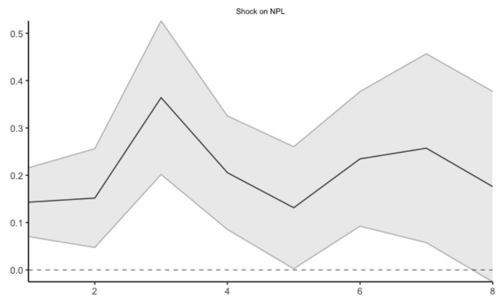
Note: The grey lines indicate 95% confidence interval.

Figure D.3: IRF - shock to NPL ratio, response of current account balance (Core)



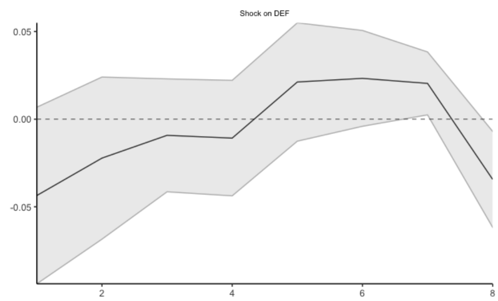
Note: The grey lines indicate 95% confidence interval.

Figure D.4: IRF - shock to current account balance, response of NPL ratio (Core)



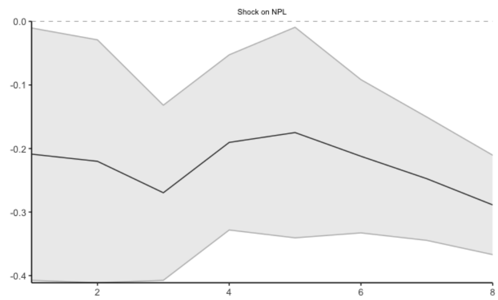
Note: The grey lines indicate 95% confidence interval.

Figure D.5: IRF - shock to NPL ratio, response of government deficit(Core)



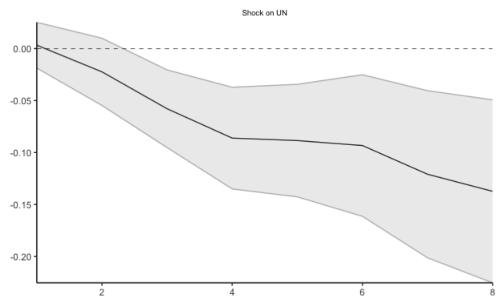
Note: The grey lines indicate 95% confidence interval.

Figure D.6: IRF - shock to government deficit, response of NPL ratio (Core)



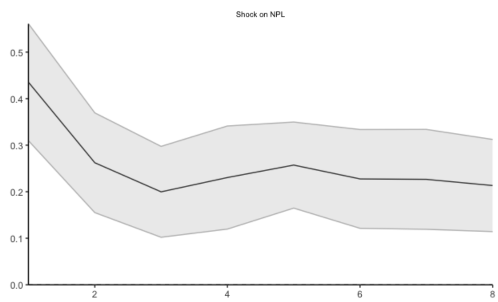
Note: The grey lines indicate 95% confidence interval.

Figure D.7: IRF - shock to NPL ratio, response of unemployment rate (Core)



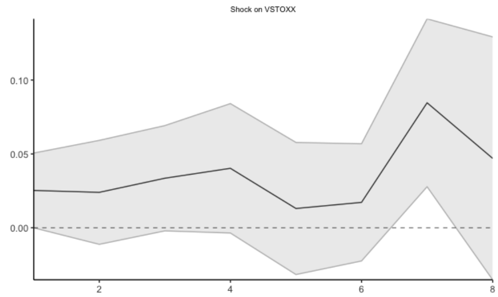
Note: The grey lines indicate 95% confidence interval.

Figure D.8: IRF - shock to unemployment rate, response of NPL ratio (Core)



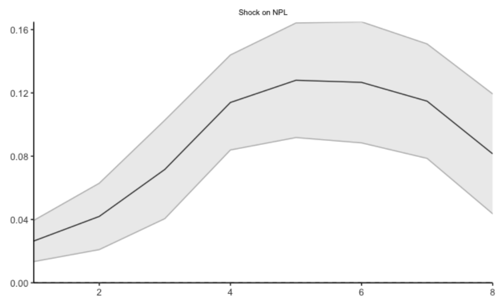
Note: The grey lines indicate 95% confidence interval.

Figure D.9: IRF - shock to NPL ratio, response of VSTOXX (Core)



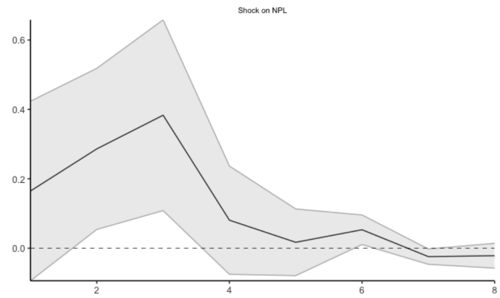
Note: The grey lines indicate 95% confidence interval.

Figure D.10: IRF - shock to VSTOXX, response of NPL ratio (Core)



Note: The grey lines indicate 95% confidence interval.

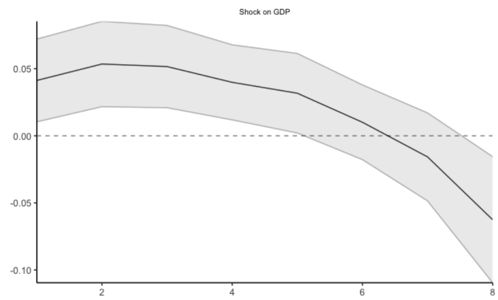
Figure D.11: IRF - shock to NPL ratio, response of NPL ratio (Core)



Note: The grey lines indicate 95% confidence interval.

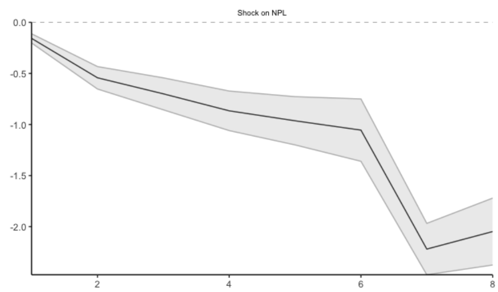
Periphery

Figure D.12: IRF - shock to NPL ratio, response of GDP growth (Periphery)



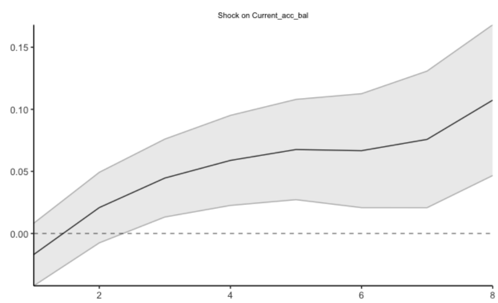
Note: The grey lines indicate 95% confidence interval.

Figure D.13: IRF - shock to GDP growth, response of NPL ratio (Periphery)



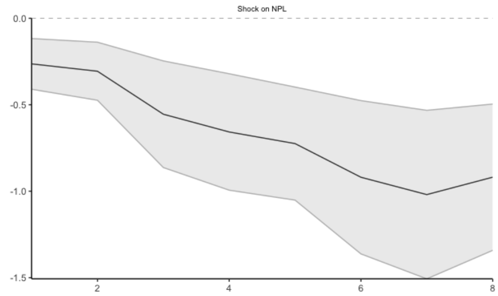
Note: The grey lines indicate 95% confidence interval.

Figure D.14: IRF - shock to NPL ratio, response of current account balance (Periphery)



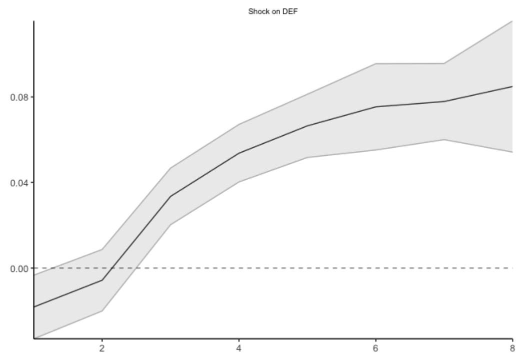
Note: The grey lines indicate 95% confidence interval.

Figure D.15: IRF - shock to current account balance, response of NPL ratio (Periphery)



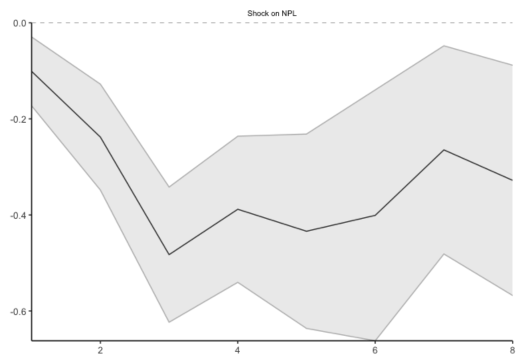
Note: The grey lines indicate 95% confidence interval.

Figure D.16: IRF - shock to NPL ratio, response of government deficit (Periphery)



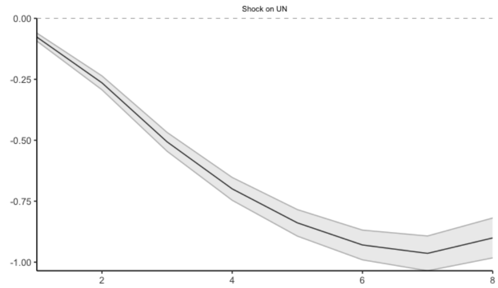
Note: The grey lines indicate 95% confidence interval.

Figure D.17: IRF - shock to government deficit, response of NPL ratio (Periphery)



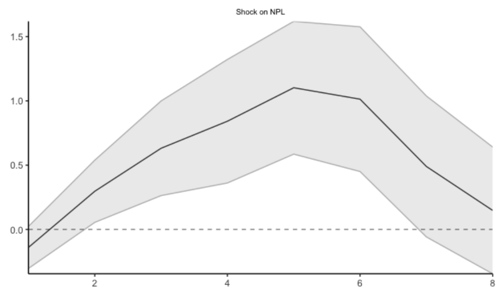
Note: The grey lines indicate 95% confidence interval.

Figure D.18: IRF - shock to NPL ratio, response of unemployment rate (Periphery)



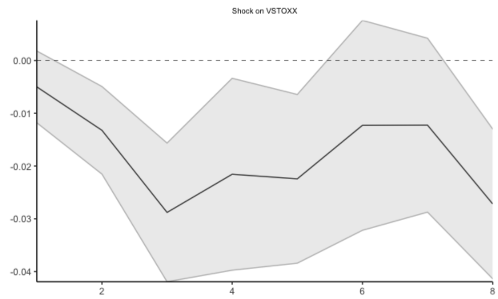
Note: The grey lines indicate 95% confidence interval.

Figure D.19: IRF - shock to unemployment rate, response of NPL ratio (Periphery)



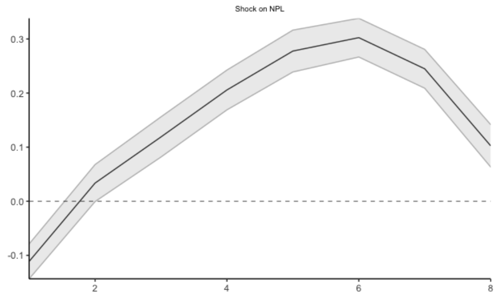
Note: The grey lines indicate 95% confidence interval.

Figure D.20: IRF - shock to NPL ratio, response of VSTOXX (Periphery)



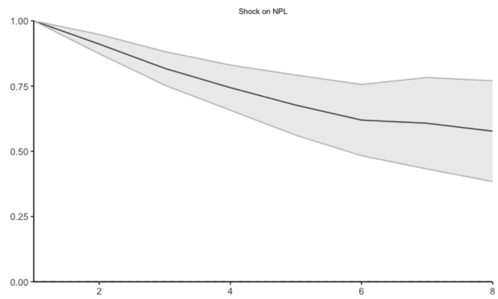
Note: The grey lines indicate 95% confidence interval.

Figure D.21: IRF - shock to VSTOXX, response of NPL ratio (Periphery)



Note: The grey lines indicate 95% confidence interval.

Figure D.22: IRF - shock to NPL ratio, response of NPL ratio (Periphery)



Note: The grey lines indicate 95% confidence interval.