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STRESS TESTING OF NON-FINANCIAL CORPORATE PORTFOLIOS OF EUROPEAN AND SLOVENIAN BANKING SYSTEMS

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MILAN DAMJANOVIĆ

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INTRODUCTION

In past and recent years the world has experienced the disruptive power of financial crises. Therefore it is not surprising that financial stability has become one of the main concerns for policy-makers and banking supervisory authorities all around the world. Financial stability can be defined as the ability of the financial system to withstand the external and internal shocks and continue to perform its key functions. It does not imply a flawless system, but a stable system with potential to recognize weaknesses and prevent them from becoming systemic. A crisis is recognized as systemic when failure of a particular institution or number of institutions important for normal functioning of the financial system occurs. The main objective of public authorities, policy-makers and banking authorities is, therefore, to build an analytical framework in order to be able to recognize the probability and severity of a potential systemic crisis. In other words, the goal is to develop the tool to *ex ante* assess the relationships between key financial and economic variables, should such instabilities occur (Quagliariello, 2009, pp. 20-22).

The tool used to assess financial stability is most commonly referred to as *macroprudential analysis*. It uses qualitative information on the institutional and regulatory framework as well as the quantitative information, where one of the key elements of the quantitative analysis is stress tests. Stress-testing analysis is therefore a part of a broader concept of assessing financial instabilities and can be defined in the context of macroprudential analysis as (Čihak, 2004, p. 2):

″...a range of statistical techniques used to help assess the vulnerability of a financial system to exceptional but plausible events″ (Čihak, 2004, p. 4).

Stress tests are forward-looking and can be therefore perceived as an early warning system. They play an important role in ascribing importance of particular economic variables for financial stability, in anticipating the potential financial instabilities, and assessing the resilience of financial systems under extreme conditions. Since stress tests have been described in the context of the macroprudential analysis, it is obvious that this thesis concentrates on system-wide stress tests or macro stress tests. System-wide stress tests refer to measuring the impact of a shock on financial system stability as oppose to stress tests for individual financial institutions (Trapanese, 2009, pp. 11-12).

The first part of the thesis is devoted to setting up a theoretical and analytical framework for a stress analysis. I define the main objectives and incentives for development of stress-testing as well as the historical and formal background under which the stress test evolved. Next, I depict a stress test analysis as a multi-step process and describe the steps a particular analyst should undertake in order to successfully conduct such an exercise. In the first part I also critically examine different methodologies that have been used in this field in recent past and compare them among countries and banking supervisory authorities. The special emphasis is put on methodologies that have been used by the Bank of Slovenia, the European Banking Authority and the European central bank.

In the second and the third part I am going to add my own contribution by performing stress tests for several European countries, including Slovenia. The second part is focused on examining the following representative European countries: Italy, Portugal, Spain, Greece, Finland, Germany, Belgium and France. The analysis is going to be based on an individual country analysis or a country-by-country analysis. The ultimate goal is to verify hypotheses regarding the effects of a shock in different macroeconomic variables on increase of the bad loan ratio. Specific macroeconomic variables of interest used in the thesis are going to be GDP growth, an unemployment rate and a short-term interest rate. For these variables a shock scenario is going to be prepared, based on which I am going to estimate growth of bad loans for the following two years. Once the growth of bad loans is estimated it will allow me to determine adequate capitalization for the discussed countries.

The third part is devoted to the application of the stress test to the Slovenian banking system. In this case, the analysis is going to be more precise in a sense that variables of interest are going to be micro bank-specific variables. The goal is to present bank-specific variables that could potentially serve as an early internal warning system from which the supervisory authorities, such as the Bank of Slovenia, would be able to assess financial stability. The purpose of this exercise is to establish which of the bank-specific variables could serve as determinants of development of bad loans and measure their impact on loan performance in case of a shock scenario.

Both, the second and the third part, are focused only on non-financial corporate portfolios, since it has been proven that non-financial corporate portfolios tend to be the most responsive and the most significant ones as far as the health of a financial system is concerned. Also, modelling different types of portfolios (i.e. mortgage loans) may require different model specifications and explanatory variables to be included in the exercise (Louzis, Vouldis, & Metaxas, 2010, p. 1;17).

The purpose of the thesis is, therefore, to set up and verify a theoretical and analytical framework for a stress-testing analysis, to demonstrate the application of different econometric models for the purpose of a stress analysis, and to determine the causality and effect of macroeconomic and bank-specific variables on performance of the non-financial corporate portfolios. The latter is of the particular importance, since microeconomic variables are rarely included in stress analyses, even though they might provide earlier and more detailed information about stability of a financial system. Aside from demonstrating a simple and useful implementation of stress-testing methodologies, the main contribution of the thesis to the financial stability analysis would be in offering new concepts that would deal with existing problems, such as bridging the gap between the micro and macro analysis, and allowing for endogenous responses and feedback effects.

In the first part, the thesis is based on a comprehensive overview of the theoretical and analytical literature, where I critically examine scientific discussions, scientific work papers and other literature on the discussed topic. This part also includes some empirical evidence. The overall approach of the first part therefore leans on a descriptive method.

In the second part, the empirical examination is based on the application of Vector Autoregressive model (VAR), a popular econometric tool useful for capturing interdependencies among multiple time series data and allows for their projections. For the purpose of assessing financial stability of the Slovenian banking system in the third part, I am going to use the Vector Autoregressive model based on panel data (PVAR). This will allow me to give estimates for the whole banking system based on the bank-specific micro variables. It will also allow me to capture potential feed-back effects of the stressed banking system on the economy. Effects of shocks in bank-specific variables and feed-back effects are going to be estimated through impulse response functions.

1 THEORETICAL AND ANALYTICAL FRAMEWORK

1.1 HISTORICAL AND INSTITUTIONAL BACKGROUND

First stress-testing exercises emerged in the early 1990s and were mostly conducted at an individual level by large international financial corporations and banks. The prevailing method used for the purpose of a financial stability analysis in the following 5 years was Value at Risk (VaR), which was widely accepted and perceived as a solution to the modern risk management problem. However, financial instabilities that followed soon revealed all major flaws of the VaR method. For example, one of the most disturbing flaws is that VaR method is extremely ignorant to tail events. It explains what is the worst loss of a portfolio over the given time horizon, in example 95 out of 100 days. However, it fails to provide the information on the remaining 5 days or those extreme events that tend to occur more frequently than they should and are actually the ones that put businesses out of work (Aragones, Blanco, & Dowd, 2008, pp. 23-24).

In comparison to standard VaR methods, stress tests are able to estimate the effects of arbitrary extreme events. Therefore, stress tests emerged as a complement to internal models for assessing risks in the 1990s. Moreover, in 1996 amended Basel Capital Accord (a set of minimum capital requirements for banks published by the Basel Committee on Banking Supervision) bounded banks and financial institutions in developing stress tests as a part of a calculation of capital requirements for market risk. The new Capital Accord named Basel II (2004) wideness the scope of stress testing to all types of risk, namely the credit risk, the interest rate risk, the foreign exchange risk, the contagion risk and others. Explanation of particular type of risk is provided in section 1.3.2. The Basel II framework has required all banks to supplement their internal risk models (for calculating capital adequacy ratio) with sound stress testing methods (Aragones, Blanco, & Dowd, 2008, pp. 17-18; Quagliariello, 2009, p. 19):

″Banks must supplement their VaR model with stress tests (factor shocks or integrated scenarios whether historic or hypothetical) and other appropriate risk management techniques. In the bank’s internal capital assessment it must demonstrate that it has enough capital to not only meet the minimum capital requirements but also to withstand a range of severe but plausible market shocks″ (Basel Committee on Banking Supervision, 2005, p. 165).

In addition to stress-testing at an individual level, in recent years stress-testing has also become increasingly used by banking and public authorities for the purpose of the financial stability assessment. Macroeconomic stress-testing has become a part of the core activities in the context of the Financial Stability Report Assessment Program (FSAP), the joint initiative by the International Monetary Fund (IMF) and the World Bank. The FSAP refers to a detailed analysis and examination of country's financial system. Financial System Stability Assessment (FSSA) Country Reports have been regularly issued by the IMF-World Bank FSAP since 2001. Furthermore, large scale financial sector simulation analyses have been a regular practice for all G-10 countries for the past 10 years. Similarly, banking and supervisory authorities in developed countries have recently adopted advanced econometric models which process micro and macro data with purpose of assessing the stability of financial systems. As far as the euro area is concerned, stress-testing methods have been adopted by most national central banks along with the European Central Banks that regularly conduct the EU-wide stress-testing (Quagliariello, 2009, p. 20; The Financial Sector Assessment Program (FSAP), 2012).

1.2 MAIN OBJECTIVES OF STRESS-TESTING

As described above, stress tests have become an important part of the internal risk management models of banks and an essential piece in financial stability assessments by central banks. Therefore, defining and understanding objectives of stress-testing is essential as different objectives may lead to a different stress-testing model. A stress test model is like any other model, meaning that it replicates the reality in an artificial environment. Thus, it is important to establish what one wants to see in a model, what is essential and what can be ignored (Drehmann, 2008, p. 61).

When defining goals of stress tests, one first needs to determine whether they are being conducted for internal or external purposes. Stress tests for an internal use usually lead to two broader objectives, *validation* and *decision making*. The former refers to the calculation of capital adequacy ratio and to models which intention is to supplement the internal risk models for determining capital, whereas the latter (decision making) refers to use of stress tests as an input for business planning by commercial banks and determination of financial system's vulnerabilities by central banks. On the other hand, an external use of stress tests leads to a different objective, which is *communication* with public. This objective is usually pursued by central banks and non-supervisory public institutions such as the IMF or the World Bank. Therefore, in cases when stress tests are intended for an internal use, practitioners will strive for accuracy and good forecast performance of models, whereas in cases of an external use the priorities will be transparency and storytelling (Drehmann, 2008, pp. 63-65).

Regardless of the model choice, derived from different objectives, stress test is always a forecasting model. However, the goal is not to forecast a regular path of future development, but to estimate the impact of extreme but still plausible shock. It is important to note that the goal of communication stress tests is not to give point predictions, but to develop early warning systems by weighting the importance of different variables in anticipating financial instabilities. Contrary, as it was already emphasized, when the goal is to quantify the amount of extra capital that banks may need in extreme but plausible market condition, the models are going to be more precise and predictions would be concentrated around a single point (Quagliariello, 2009, pp. 65-66; Drehmann, 2008, p.22).

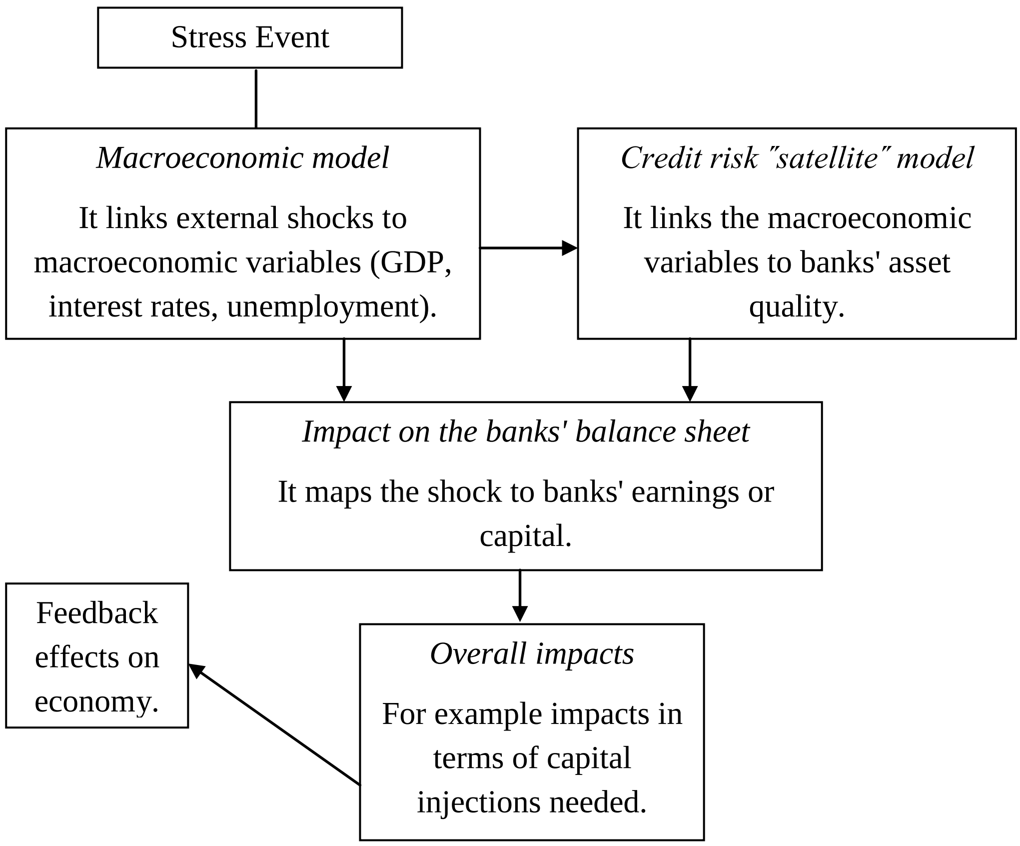
The main objective of macroeconomic stress tests is to identify systemic vulnerabilities and to assess the resilience to shocks. It is important to emphasize that the goal is not to pursue zero-failure economic world, but to try to prevent discussed vulnerabilities from becoming systemic. The goal is also not to prevent problems and shocks from materialising, but rather to protect the stability of the banking system and minimise the impacts of those shocks. The triggering shocks may be the least interesting ones as they are usually detected too late to be a leading indicator. It is important to recognize fragilities through financial soundness indicators and their relationships to a given portfolio in a stressed situation. The objective of central banks and supervisory authorities should therefore be to build a framework through which the shocks and severity of their impacts is recognized as soon as possible (Trapanese, 2009, pp. 8-9).

1.3 STRESS-TESTING, A MULTI-STEP PROCESS

In line with the FSAP, macroeconomic stress tests are most commonly designed in a multi-step process as depicted in Figure 1. The first step in building a stress test is to design a proper (macroeconomic) stressed scenario. This is usually done by setting up a **macro-econometric model** (particular models and methodology used by different central banks are described in sub-section 1.4) through which one can reflect adverse economic conditions. The model would typically characterize linkages among representative macroeconomic variables such as: GDP, interest rates, unemployment, exchange rates, and others. These variables can be stressed individually or simultaneously, where in the latter case one can talk about a multivariate stress scenario (Foglia, 2008, pp. 6-7; Čihak, 2004, pp. 2-3).

Given that such macro-econometric models do not generally include financial sector variables that would directly link a macroeconomic shock to banks' asset quality, practitioners have to include the **satellite model**. They are used to map an external adverse macroeconomic scenario (slowdown in GDP growth, rise of interest rate or rise in unemployment) to financial sector variables that indicates banks' asset quality (rise of write-offs ratio, rise of non-performing loans), through which the impact on a balance sheet in terms of capital can be determined. This kind of a structure is considered to be questionable by some practitioners since it demonstrates a model based on a model approach. This can be overcome by using, for example, models based on the impulse response functions, where variables measuring banks' asset quality can be instantly incorporated in the macroeconomic model, meaning that one can omit the intermediary step of including an extra linking model (this is demonstrated on case of Slovenian banking system in section 3) (Čihak, 2007, pp. 7-8).

Figure 1: Stress-testing, a multi-step process



Source: Antonella Foglia, Stress Testing Credit Risk: A Survey of Authorities' Approaches, 2008, p. 6; Martin Čihak, Introduction to Applied Stress Testing, 2007, p. 8

Deterioration in a balance sheet often demands from public authorities to take measures in terms of capital injections in order to recapitalize banks. This has direct impact on the public budgets and thus the overall economic activity. Further, reduced earnings and capital along with deteriorated portfolio structure, reduced confidence in the banking system and consequently causes additional feedback effects through induced a credit crunch (Čihak, 2007, pp. 8-9).

Aligned with the above stress-testing structure broader and more detailed description of the stress-testing process can be derived. Namely, to fully implement a stress test, the particular practitioner must go through several stages: defining coverage (institutions or banks to be included) and data, identifying major risks, determining risk measures, calibrating shocks, implementing scenarios, implementing methodology, and interpreting results (Čihak, 2004, p. 8).

1.3.1 COVERAGE AND DATA

The first step in designing a system-wide stress test is to determine the coverage of banks or financial institutions to be included in the analysis. Selecting the whole banking system is usually too wide and extremely burdensome. While this might not be the case for the Slovenian banking system (25 banks), it certainly has different implications in case of the German banking system which consists of almost 1900 banks. Therefore, it is advisable to include core institutions or systemically relevant banks that are likely to be affected by common risk factors. The most common criterion used to determine systemically important banks is size, in terms of assets or market share (loans of an individual bank compared to the whole loans of a banking system). Stress tests mostly cover banks since they dominate most financial systems, however, sometimes also other financial institutions such as insurance companies are included (Čihak, 2004, p. 8).

The system-wide stress testing need not necessarily be performed on aggregate data. With aggregation of data there exists a risk of not controlling for substantial exposures of individual institutions and consequently not controlling for contagion to the rest of the system. Therefore, it is preferred to perform stress tests on an institution by institution's basis to the highest extent possible. This can be done by performing so called panel data analysis, which I demonstrate on a case of the Slovenian banking system in chapter 3. In other words, this means that the coverage also depends on whether public authorities and central banks use bottom-up or top-down approach (Čihak, 2004, pp. 4-5).

1.3.1.1 BOTTOM-UP AND TOP DOWN APPROACH

In case of the bottom-up approach, performing stress tests is left to individual banks themselves and data on individual portfolios are used. The supervisor or central bank approves the methodology, sets the assumption on future macroeconomic conditions, and collects the results of stress-testing exercises conducted by banks under its supervision. Contrary, in the top-down case, the central bank decides on the assumptions about the economic outlook and also performs a system-wide stress test on aggregated data. The main feature of the top-down approach is that it applies the same assumptions and methodologies to all banks, which can be beneficial as the results obtained are easily comparable. However, the top-down approach fails to control complexities and usually suffers from data limitation since the detailed data on exposures to individual borrower might only be available to individual banks. The bottom-up approach is usually capable to detect the concentration of risk and contagion, which gives more precise and accurate results. But as mentioned, the bottom-up approach usually does not offer comparable results, since it allows for greater flexibility in terms of models and data used, and usually deals with great computational barrier, especially in large and complex systems (Čihak, 2007, pp. 12-13; Vukelić, 2011, p. 9).

Examples of the top-down approach can be found in stability reports of the Bank of England and the Norges bank, whereas for example the Austrian National Bank relies more on the bottom-up approach. Nevertheless, most central banks and other institutions rely on the combination of both approaches, which I also attempt to do in the third chapter, where the Slovenian banking system is discussed (Čihak, 2007, p. 13).

1.3.2 IDENTIFIYING MAJOR RISKS

One of the initial stages of designing a stress test is first to recognize the types of exposures and potential shocks arising from them. Most common types of exposures for the banking system are **credit risk**, **market risk**, **liquidity risk**, **contagion risk**, **concentration risk**, and others (Čihak, 2007, p. 10; Vukelić, 2011, pp. 11-12):

Credit risk: Refers to the failure of the counterparties (debtors) to fulfil their obligations.

Market risk: Refers to the deterioration of the balance-sheet position due to the adverse market movements (adverse changes in stock prices, interest rates, foreign exchange rates, commodity prices, and others).

Liquidity risk: Risk that banks' liabilities cannot be met, because the market inactivity prevents banks from realizing their assets.

Contagion risk: Refers to the impact of failure or downgrades of one or more financial institutions on the other banks or institutions.

Concentration risk: Refers to the low portfolio diversification, and thus to high exposure to a particular subject (debtor, sector, product, and others).

In practice, analysts decide on type of exposure based on the activities and characteristics of their banking systems. For example, when banks are oriented mainly on the domestic loan market the practitioners should place emphasis on credit risk and risk factors arising from it (interest rates, unemployment, real estate prices, and others). If banks are also internationally active, market risk would probably be more relevant as it captures factors such as oil and raw material prices, exchange rates and other similar factors. In case of a small banking system, the contagion risk would be of a great relevance as banks are interconnected with institutions in other countries, meaning that also exchange rate risk falls into consideration. Liquidity risk can be considered when banks are involved in significant wholesale funding (method that banks use, besides core deposit activity to support daily operations) from abroad or lack deposit insurance at home. The thesis is focused on examining the credit risk, as it is the majority of literature on the topic of stress-testing analysis (Quagliariello, 2009, pp. 27-28; Lopez-Espinosa, Moreno, Rubia, & Valderrama, 2012, p.3).

1.3.3 DETERMINING RISK MEASURES

Risk measures are the variables used to evaluate the impact of a stress test. In other words, they can be considered as **financial soundness indicators (FSIs)** under stressed conditions. As the name states, the FSIs are a set of variables that measure the soundness of financial or banking systems. Practitioners choose those variables based on the objective of stress testing and type of exposure considered. In 2001 the IMF issued a list of core and encouraged FSIs. The list of core FSIs was determined in a way to capture banks' capital adequacy, asset quality, earnings and profitability, liquidity and sensitivity to market risk:

Table 1: Core financial soundness indicators

Capital adequacy	Regulatory capital to risk-weighted assets Regulatory Tier I capital to risk-weighted assets
Asset quality	Nonperforming loans to total gross loans Sectoral distribution of loans to total loans
Earnings and profitability	Return on assets Return on equity Interest margin to gross income Noninterest expenses to gross income
Liquidity	Liquid assets to total assets Liquid assets to short-term liabilities
Sensitivity to market risk	Duration of assets Duration of liabilities

Source: Financial Soundness Indicators (FSIs) and the IMF, 2011

The FSIs related to capital adequacy are intended to assess the capacity of the banking sector to absorb losses, while other categories are intended to capture vulnerabilities arising from credit, liquidity and market risks. Since my thesis is focused on credit risk, the FSIs that would be of particular interest are those related to the assessment of the asset quality. Practitioners usually choose variables from particular FSI category based on the data availability, ability to easily interpret the variable as the measure of financial system's health, and ability to link variables to the risk factors (Čihak, 2007, p. 14; Vukelić, 2011, p. 13).

For the purpose of the empirical exercise for the European banking systems I use write-offs[1] to total loans ratio, while in the case of the Slovenian banking system I use non-performing loans to total loans ratio[2]. Both measures are intended to identify problems with asset quality in the loan portfolio.

1.3.4 DESIGNING SCENARIO AND SHOCK CALIBRATION

After the major risks have been identified, the scenario that depicts the implementation of these risks has to be designed. Setting the severity of shocked scenario too low or too extreme may cause the whole stress-testing exercise meaningless, since the obtained results are therefore misleading and useless for policy-making process. The usual condition, when designing a stress scenario, is therefore ″extreme but plausible″. However, defining the

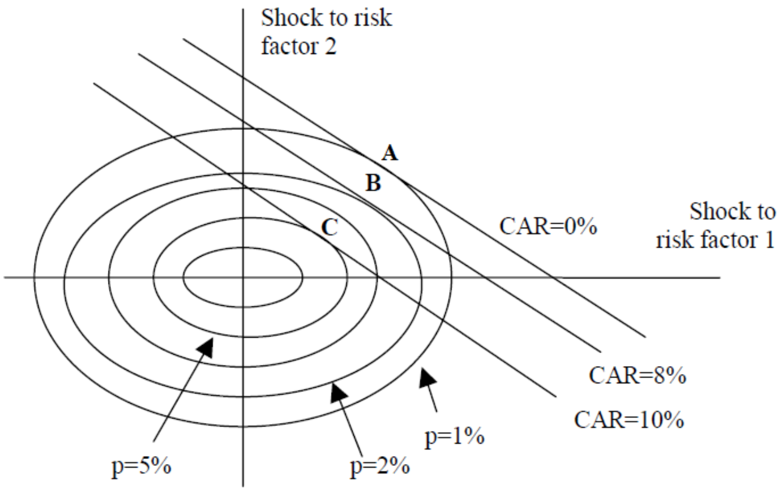
[1] Assumptions on behaviour of write-offs are presented in the empirical part, where stress-tests for European banking systems are conducted.

[2] Assumptions on behaviour of write-offs are presented in the empirical part, where stress-tests for European banking systems are conducted.

plausibility of a shock event remains a challenge, and is often subject to practitioner's personal judgement. Some objectivity can be imposed by setting up such as the ″once in n years event″ condition. This condition is usually complied with developing historical scenarios, where shock can be calibrated based on the distribution of past observations. For example, a 3 standard deviations shock in GDP, which can also be expressed as 99 % values on the confidence intervals (Isogai, 2009, p. 70).

Such approach as described above can also be referred to as **the worst case scenario**. It can be defined as the shock scenario that minimizes the value of a portfolio at a given size of plausibility. This means that a scenario is basically designed by predefining the minimum level of plausibility (in upper case the minimum level of plausibility would be 1 %). Čihak (2004, p. 10) offers illustration of this approach (see Figure 2). The ellipses depict all possible combinations of two risk factors (i.e. GDP and interest rate) that have a same level of probability of occurrence in a given scenario. The plausibility of scenarios diminishes with larger ellipses. The diagonal lines indicate the level of the impact at a given combination of the two risk factors. The combination of the two factors where the diagonal line is a tangent on ellipse indicates the maximum level of impact in a selected scenario. In the worst case scenario, one would first select the level of plausibility (i.e. 5 %) of event (combination of GDP and interest rate) occurring and then determine the worst impact (point C).

Figure 2: The worst case and threshold approach to scenario design



Source: Čihak, Stress Testing: A Review of Key Concepts, Figure 2

As mentioned the worst-case scenario is usually implemented through backward-looking historical scenarios. But these kinds of scenarios have some setbacks, for example, they only work under the assumption that financial systems do not exhibit any structural changes in terms of legislation, deregulation, change of currency, and others. Even if extremely long time series data is available, it is useless if it does not account for such structural breaks. Therefore, there is a growing need for design of hypothetical scenarios that would include plausible events that have not yet happened. Like a historical scenario, a hypothetical scenario is also based on some probability, but the probability distribution differs from the one obtained from past observations (Isogai, 2009, p. 71; Čihak, 2004, p. 11).

One way to design a hypothetical scenario is by employing **the threshold approach** as it was demonstrated by van den End Hoeberichts and Tabbae (2006, pp. 2-3). As the name implies, in the threshold approach one would first select a threshold (diagonal line in Figure 2) and then search for the smallest shock reaching this threshold (in other words, finding a point where selected diagonal is a tangent to ellipse). For example, one could be interested in the largest increase of the non-performing loans that would still leave banks adequately capitalized. The threshold approach can also be referred to as **the catastrophic scenario** approach, since it also reveals the largest possible shock at a given plausibility that would exhaust all of banks' capital (point A in Figure 2) (Čihak, 2004, p. 10).

1.3.5 METHODOLOGY SELECTION AND IMPLEMENTATION[3]

Before discussing methodology it is worth noting that there is no unified or formal approach to estimate the magnitude of losses once the shock is materialised. This means that practitioners must again understand the objectives in order to decide on what is really important to be captured and what can be ignored. As it has already been explained, different objectives (whether the goal is decision-making or communication) can lead to different methodology choices. Depending on the interpretation preferences, the description of relationships among risk factors and loan performance variables may be of greater interest than giving the exact point predictions. For example, autoregressive models have proven to provide a really good forecast performance, but tend to offer little in terms of communication or policy evaluation (see sub-section 1.4). These kinds of trade-offs, combined with data availability, will lead to different methodology selection and model specification (Drehmann, 2009, p. 38).

When choosing methodology, one should make sure that it is consistent with the already discussed objectivity of extreme but plausible assumption. This means that one should pick a method that would be able to produce extreme outputs, but would still remain imaginable. Usual way to approach this is by applying extreme value theory (EVT) based methods, which focus on producing estimates from the tails of the distribution of historical data. Another simple solution would be to run multiple scenarios with different degrees of severity for the same risk model and then find an extreme but plausible scenario from a set of the same scenarios with a different degree of severity (Isogai, 2009, p. 77).

1.3.6 INTERPRETATION OF RESULTS

As it was already depicted by Figure 1 and Figure 2, the deteriorated asset quality is most commonly interpreted through eroded reduced profit earnings and eroded banks' capital. Pre-tax profits can be interpreted as the bank's first line of defence and can be described as the income available for absorbing the extra losses arising from stress events. The eroded

[3] For more on the methodology and particular model examples see sub-section 1.4.

banks' capital, on the other hand, may cause banks not to meet regulator's minimum requirements, meaning that they do not meet sustainable capital adequacy ratio in order to absorb potential losses. The capital adequacy ratio is estimated by dividing eroded regulatory capital with risk weighted assets (RWA). For example, the loans secured by a letter of credit will be weighted riskier as the mortgage loan secured with collateral. I provide a detailed explanation on banking system capitalization in subsection 2.3, in a practical example for the European countries. Dividing capital with RWA enables comparison among institutions or among countries of a different size. However, looking just at the aggregate impacts may hide some important pieces of information on the consequences of the shock event. For example, it is possible that two different scenarios reflect similar capital adequacy ratios, while in one case all banks remain solvent, in another case a mayor systemic bank may go under regulatory minimum. Therefore, the actual figures should be weighted also by the size of the affected institutions, which can only be done if test is run on bank-by-bank basis (Quagliariello, 2009, pp. 34-35).

1.4 OVERVIEW OF METHODOLOGY

In subsection 1.3 it was stated that stress scenarios are usually designed through a macro-econometric model. More specifically, there are three varieties of models through which adverse macroeconomic conditions can be estimated: **structural econometric models**, **vector autoregressive models**, and **pure statistical approaches**. Some central banks use the combination of listed approaches (Foglia, 2008, p. 7).

Structural econometric models are central banks' internal models used for projections of the macroeconomic variables and policy analysis (i.e. Dynamic Stochastic General Equilibrium model). They combine the economic theory with statistical and econometric models. Considering the fact that they build on the economic theory and assumptions makes them more suitable for communication purposes and policy decisions. Shocks step into the model as exogenous variables, which in interaction with macroeconomic variables produce projected outputs (GDP, interest rates, unemployment, the exchange rates, and others) over the given scenario horizon. Often these macro models do not include financial variables such as housing prices or stock returns, meaning that central banks use additional unstructured models for projections of those variables. Structural econometric models are mostly concentrated on domestic economies, meaning that for the purpose of stress-testing exercises additional variables (i.e. foreign GDP) have to be added in order to capture international effects. Designing adverse macroeconomic scenarios through structural econometric models is a regular practice of the following central banks: Bank of Canada, Bank of Italy, De Nederlandsche Bank, Deutsche Budnesbank, Banque de France, Norges Bank, and Sveriges Riksbank. In the context of the FSAP exercise, structural econometric models were employed by all authorities participating (Reiss & Wolak, 2007, p. 4282; Foglia, 2008, pp. 7-8).

In cases where structural macroeconomic models are not developed enough to produce consistent relevant shocks or when there is little economic theory to build on, practitioners may prefer to use unstructured or descriptive models. One such option is to use **vector autoregressive models (VAR)** or **vector error correction models (VECM)**. These models produce joint projections of multiple stressed variables. VAR models are flexible in terms of adding new variables and are very easy to interpret. However, they offer little in terms of story-telling since they are lacking economic theoretical background. The advantage of the VAR models is that, unlike structural models which give point predictions connected with a single future path, VAR models generate predictions that do allow for probabilistic interpretation (flexibility in terms of extreme scenario choice). For example, shocks can be expressed as standard deviations or values picked from confidence intervals (i.e. values with probability 1 %). Therefore, these extreme values can be interpreted as tail outcomes and have no economic reasoning included as in structural macro models. Central banks that design adverse macroeconomic scenarios by using VAR models are the following: the Bank of England, the Bank of Japan, the Bank of Spain, De Nederlandsche Bank, the European Central Bank, the Bank of Greece, and others (Foglia, 2008, p. 8).

Another option for scenario design is the case of the Oesterreichiche Nationalbank, which is based on a **pure statistical approach**. The approach joins the distributions of particular macroeconomic and financial variables that are to be stressed into a joint distribution, forming the distribution copula. Since the distributions of variables are not normal but student-t distributions, the copula is named t-copula. The tails of the t-copula represents the combinations or correlations of variables which can be interpreted as different scenarios at a given probability. The t-copula approach has one major advantage in sense that the tail dependencies or correlations among variables increase in a stressed scenario, whereas in the structural and VAR models those relations are linear throughout. However, the major disadvantage is that as a pure statistical approach it is very complicated to interpret transmissions from shocks to impact (Oesterreichische Nationalbank, 2006, pp. 17-20; Foglia, 2008, p. 9).

Most common variables used in macro scenario design are GDP growth, short-term or medium-term interest rate, and unemployment. Other macro-economic and financial variables may also be included depending on a particular national central bank. For example the Bank of Italy includes also equity returns and competitiveness index variables in the model. Equity returns variable is also included in models of the Bank of England and ECB. Another frequent variables included are also consumer price index CPI, exchange rates and credit growth (i.e. the ECB or Deutsche Bundesbank). The Austrian model also includes variables like oil prices, industrial production rate and investment in equipment (Foglia, 2008, p. 9).

In almost none of the country cases scenario design credit risk variables are directly included in the model, meaning that additional satellite models need to be included in order to map stressed macroeconomic variables to credit risk indicators. Exceptions are those VAR models where shocks are implied through impulse response functions. Impulse response functions are used to examine the effects of a shock in a particular macroeconomic variable on the credit risk variable and other macroeconomic variables[4]. These models are particularly appealing because they also allow for potential feedback effects on macro-economy (i.e. a credit crunch and a drop in GDP). This is not the case in the satellite model where stressed macroeconomic variables are treated as exogenous. VAR models with the use of impulse response functions have been used in stress-testing exercises conducted by the Bank of Japan, the Bank of Spain, the ECB, the Bank of Greece and others. Based on how one can map macroeconomic variables to credit risk indicators, the methodology can also be divided to models based on loan performance data and to models based on individual borrower data (Foglia, 2008, p. 10; Čihak, 2007, p. 16).

1.4.1MODELS BASED ON LOAN PERFORMANCE DATA

Models based on loan performance data measure the sensitivity of key loan performance variables to adverse macroeconomic condition. The loan performance variables are usually NPL ratios, write-offs ratios, LLP ratios, default rates, and others. As explained, the sensitivity can be measured by regressing loan performance variables against exogenous macroeconomic variables (satellite models) or through impulse response functions, where all variables are treated as endogenous. Besides macroeconomic factors, also variables related to creditworthiness of firms (i.e. indebtedness of the non-financial sector) or market indicators (i.e. equity prices or corporate bond spreads) are ever more used in the models. Usually analyses are based on aggregate data for both, loan performance and macroeconomic variables. However, using aggregate data automatically assumes that the quality of a credit portfolio is the same for all banks in the system, even though some banks may pursue riskier strategies. The way to overcome this problem is to conduct an analysis based on panel data. Panel data analysis can identify bank-specific or country-specific characteristic through fixed effects[5] (Drehmann, 2009, pp. 39-40).

An example of this kind of an analysis was conducted by Louzis, Vouldis, & Metaxas (2010), who examined macroeconomic and bank-specific detirminants of NPLs by using panel the VAR method[6] for 9 largest Greek banks. Bank-specific variables used in the analysis were the following, return to asset, return to equity, credit growth, solvency ratio, market power, size, and operating expenses. Simmilar methods were used in study by Espinoza & Prasad (2010), where behaviour of NPLs were examined for 80 banks in GCC[7] region. Again macroeconomic shocks to NPLs where examined along with firm-specific variables related to risk taking. Another paper, done by Lehman & Manz (2006), studies the effects of macroeconomic shocks on profitability for the panel of Swiss banks, where this

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[4] Impulse response functions are explained and applied to a practical example in section 4, where Slovenian banking system is examined.

[5] See sub-section 4.3.2.

[6] Same method is used in section 4 for purpose of examination of Slovenian banking system.

[7] Gulf Cooperation Council refers to the political and economic union of Arab states.

time LLPs are used. LLPs are also used in the work of van den End, Hoeberichts, & Tabbae (2006). Historical defualt rates by industries can be found in stress-testing exercises done by the Bank of Spain or for example the Oesterreichische Nationalbank. Macroeconomic factors affecting write-offs were examined in the paper by Lye, Loh, & Tan (2002) (Drehmann, 2009, p. 40).

The main issue of using loan performance data is that they are a lagged indicator of asset quality, meaning that they reflect past shocks. Another disadvantage is that classification of NPLs and write-offs as well as the rules on loan loss provisioning may vary across different jurisdictions and banking systems (Foglia, 2008, pp. 11-12).

1.4.2 MODELS BASED ON INDIVIDUAL BORROWERS DATA

Models based on individual borrowers data relates the probability of defualt (PD) to the individual borrower characteristics such as corporate earnings, liquidity, financial state, ratings, and others. It means that this approach explains a default through an endogenous process as defaults being a function of firms' fundamentals, especially the balance sheet. These kinds of credit risk models require no scenario design analysis (Castrén, Fitzpatrick, & Sydow, 2009, p. 5). The basis for this approach can be found in **Merton's model for credit risk** developed in 1974. In this model market and macroeconomic variables are first linked to the corporate return on equity which are then used in Merton's equation in order to convert them into probability of default. It assumes that a firm defaults when its assets drop under its liabilities (debt), or in other words when a firm exhibits negative equity returns. By accounting for volatility and expected return on firm's assets one can then measure the distance to the point (in asset distribution) where firm's assets drop under its debt. The difference between expected returns on assets and default point can then be converted into PD. By doing the panel analysis one can then obtain the overall corporate PD and thus estimate the quality of a given portfolio in a macro stress test. This methodology was used for example in Drehmann (2005, p. 9), who used a simple Merton model in order to stress test UK banks for corporate exposure. A key finding of this work is that macro variables have significant non-linear impact on credit risk. Another work using the same methodology is by Pesaran et al. (2005, p. 7), where asset value changes of firms are linked to the global macroeconometric model, in which macro effects are implied through variables such as inflation, GDP, stock index, interest rates, exchange rates, and othres. Interestingly, they find GDP to have no significant effects (Drehmann, 2009, pp. 41-42; Vukelić, 2011, p. 21).

Another simmilar approach which can in essence be cathegorized as the commercial application of Merton model is to use Moody's KMV expected default frequencies (EDFs). The EDFs are proxies for the PDs and are measured based on volatilities of firms' share prices. Sommar and Shahnazarian (2009, pp. 91-94) estimate the VECM model in order to establish the inter-dependency relations between the aggregate Swedish EDFs and three macroeconomic variables, namely industrial production index, consumer price index, and short-term interest rate. They found that the short-term interest rate has the strongest and positive effect on EDFs, meaning that lower interest rate reduces EDFs. A simmilar exercise was also conducted by the Castren et al. (2009, p. 5), where EDFs of the Europan companies at sectoral level are related to five macroeconomic variables in VAR impulse responses context. Impulse related shocks include GDP, stock prices, long-term and short-term interest rates, and the exchange rate. Shocks are regressed to sector specific PDs in the second step. Unlike Sommar et al. (2009), where interest rate was the strongest driver, they found the strongest effects in the GDP and stock prices shocks.

Merton based models can be classified as structural models, since they relate default rates to firm's balance sheet (assets and equity) structure. Contrary, there also exist reduced form models, which do not build on firms' asset and its capital structure. The reduced form models are implemented through the so called Credit Metrics, which measure the probability of borrowers migrating to a different credit quality class with respect to a given number of macroeconomic variables. In the case of French Banking Comission, which uses this methodology, the macroeconomic variables used are GDP and short term and long term interest rates. Simmilarly, the Bank of Japan uses GDP and leverage ratio, where system of 5 equations (one for each credit quality class) is estimated (Castrén, Fitzpatrick, & Sydow, 2009, pp. 10-11; Foglia, 2008, p. 13).

The main advantage of the models based on individual borrower data is that they are able to detect difficulties in the quality of banks' portfolios much earlier than models based on loan performance data. Another advantage of models based on individual data is that they lead to more accurate results. However, they often encounter data limitation and are therefore restricted to a particular set of listed companies (Foglia, 2008, p. 13).

1.4.1 MACRO STRESS TESTS IN SLOVENIA

Macro stress tests in Slovenia are based on the top-down approach and are conducted in two parts. In the first part banks’ balance sheets are stressed against the shocks in GDP, interest rate, a liquidity shock, and a liquidity shock with increased risk premium. Balance sheet items that are subject to stress events are pre-tax profits, return on equity (ROE), capital adequacy, credit growth, deposits, and rate of foreign borrowing. Shocks in GDP and interest rates are designed in the way to capture the largest historical changes (largest decline in GDP and largest increase in interest rate) at 5 % significance level (largest possible increase in interest in 95 out of 100 days). Liquidity shock is induced by assuming that foreign bank financing is no longer available for Slovenian banks. In addition to that, when foreign financing stops, increase in risk premium is assumed, meaning that existing foreign indebtedness becomes more costly. One of the key findings of the Bank of Slovenia is that credit growth is most sensitive to shock in interest rate (drop in credit demand) and quickly followed by the liquidity shock (drop in credit supply). Interest rate also represents the highest shock when profits are concerned. This means that interest rates have proven to have much higher influence on the stability of the banking system than GDP (Banka Slovenije, 2007, pp. 1-20).

The second part of performing stress tests under the Bank of Slovenia relates to analysing the credit risk. The analysis of credit risk is based on the individual borrower data and the methodology is very similar to ones described in the cases of the Bank of Japan or the French Banking Commission, where the quality of credit portfolios is assessed based on the customer credit ratings. The borrowers are ranked into five categories from A to E based on the assessment of the financial status of debtor and ability to repay liabilities. The essence of the analysis is in calculating the probability of a particular borrower ending in a certain rating class in the given future time horizon. The probability is calculated by employing the random-effect multinomial ordered probit model, with credit rating as a dependent variable and eight independent variables (borrower's capital distribution, liquidity of a borrower, change in liquidity, the proportion of cash flow from operations in revenue, short-term borrowing in the previous year, a change in demand, demand in the previous year, and ratio of selling and input prices). The model designs intervals for each credit rating category based on the critical values calculated within the model. Based on the selected indicators (independent variables), borrowers are classified in a different credit rating category. The stress is induced through shocks in short-term borrowing and liquidity (shock in terms of reduced income per sold unit). Again shocks are simulated by the worst historical observations at 5 % significance level. It has been observed that the liquidity shock has a greater impact on credit risk than increase in short-term borrowing. The migrations of the borrowers among credit rating classes are presented by the so called transition or credit metrics. The key finding of the credit analysis has been the procyclical behaviour of Slovenian banks at categorizing their borrowers, meaning that they rate the borrowers more optimistically in the sound economic times, even though the characteristics of a borrower may not change significantly. This means that banks tend to reduce the initial borrower rating already after one year, whereas in the longer periods the migration intensifies even more (Banka Slovenije, 2007, pp. 22-30; Kavčič, 2005, 10-14).

1.4.2 EUROPEAN MACRO STRESS TESTS

The European Banking Authority (EBA) conducts an EU-wide stress-testing exercise on an annual basis. The test is focused on assessing banks’ statements in a bottom-up manner, meaning that assumptions on adverse macroeconomic scenarios are provided by the EBA, whereas the application of scenarios to balance sheet items is left to banks' internal models. The methodology used by individual banks has to be submitted to national central banks which are responsible for quality assessment based on the country’s benchmark obtained by the ECB in a top-down manner. In 2011 the adverse macroeconomic scenario was composed of a set of EU shocks (mostly tied to ongoing sovereign debt crisis) and shocks related to non-EU development such as the global negative demand shock originating in the US or USD depreciation vis-a-vis all currencies. The aggravation of an ongoing EU-sovereign crisis was expected to affect countries’ macroeconomic outlook by affecting several asset prices, increasing uncertainty, tightening credit condition, which reflects in deterioration of macroeconomic indicators. Shocks are then distributed proportionally across countries. For example, country-specific bond yields are forecasted based on the recent volatility of sovereign credit default swap spreads[8]. Similarly, a fall in stock prices for example is also calibrated according to the recent volatilities in national stock indexes. Similar procedures are applied to calculate several other shocks like a shock in housing prices, a shock in inter-bank interest rates, a shock in consumption and investments, and others. Combining these EU shocks and non-EU developments is then translated into macroeconomic indicators, namely the GDP, the inflation rate and the unemployment rate for each country. Banks are also required to consider substantial lags observed between the occurrence of the macroeconomic shock and its translation in increased defaults, losses or other adverse outcomes in balance sheets (EBA, 2011, pp. 1-20; 45-47).

Many EU-wide stress test exercises have also been performed by the ECB. From the methodological point of view the most interesting is probably the one from Castren, Dees and Zaher (2008, pp. 8-13), where adverse macroeconomic scenario is designed by using the Global Vector Autoregressive (GVAR) model. The GVAR model is composed of individual country VAR models, where each model is connected to others by including foreign-specific and global variables vectors. This means that an individual model connects a set of domestic macroeconomic variables (domestic GDP) to their foreign counterparts (foreign GDP), specific to the respective country trading patterns. Aside from the direct linkages between domestic and foreign variables (including their lags), the international linkages among countries are also insured through incorporation of an exogenous global variable vector and by cross-country covariance. Individual model estimates are connected through link matrices and stacked together in order to construct the GVAR model. The GVAR model then represents the right-hand side of the satellite model (the left hand side variable is Moody's EDFs) with the following variables: real GDP, stock market return, inflation, short-term and long-term interest rates, oil prices, and exchange rate. Although the right-hand side includes only euro-area variables, the international effects are accounted for in the GVAR model through channels described above (Galesi & Lombardi, 2009, pp. 10-15; Foglia, 2008, pp. 9-10).

1.5 METHODOLOGICAL CHALLENGES

So far I tried to show the stress-testing process and offer examples on the methodology used. However, every practitioner encounters important challenges along such a process. Those challenges could be categorized into four major groups, namely the **data limitations**, the **endogeneity of risk** connected to central banks' policy responses and to macro feedbacks, challenges connected to **non-linearities** of the stress-process, and challenges connected to the assumptions made on distributions of risk factors.

1.5.1 DATA LIMITATION

Challenges connected to data limitation were partly discussed in the previous sub-sections. As mentioned, practitioners usually face short time series and thus the scarcity of extreme

[8] Credit Default Swap (CDS) is basically the insurance on debt, where the seller of the CDS obliged itself to compensate a Buyer of the CDS in case of the default of loan that Buyer issued to the third party.

observations. It is not surprising then that every financial meltdown brings along scenarios that have not yet happened and which latter turn out to be more plausible than they were initially predicted. In addition to that, financial markets are overwhelmed with rapid and ongoing innovations, with products and agents emerging continuously, where models are just incapable of tracing that. Short time series and lack of data lead to large errors in the estimation process, especially as the focus of stress tests are the tails of distribution. The problem only increases if we take into consideration that most exercises induce a model based on model approaches, where errors only multiply, when estimates are carried from macroeconomic models to the satellite models. When dealing with that, one should therefore be careful about giving exact point predictions (Drehmann, 2008, p. 75; Isogai, 2009, p. 71).

Applying disaggregated data to the panel analysis or considering different econometric methods would in many instances reduce the error of estimation and improve the stress-testing model. Another thing that would also help to enrich the analysis is to surpass the backward-looking mindset and to consider designing hypothetical scenarios. One possible way of doing that is through the threshold approach (explained in the subsection 1.3.3), or through EVT properties of examining fat tails, where it is possible to estimate the probability of an extreme event that has never been experienced yet (ECB, 2006, p. 129; Drehmann, 2008, p. 76).

1.5.2 ENDOGENEITY OF RISK

Endogenous behavioural responses of private banks and central banks cause an exogenous shock to have disproportional impacts. Usual stress test models assume that agents are passive once the shock occurs, which would basically mean that they sit on their initial portfolio allocation without trying to hedge for losses or realign their portfolio. Endogenous behaviour can also be considered for central banks. In a reduced model form, the average past responses of central banks are embedded in historical changes of the market prices. The latter are result of a stress event as well as of central banks' liquidity interventions. One could then run a similar scenario where same central banks' reactions would be assumed. However, if a stress test is conducted by a central bank itself with an aim to estimate the robustness of financial system without policy interventions, this may cause a challenge itself (Drehmann, 2008, pp. 77-79).

The endogeneity of risk can also be due to the macro feedbacks. Absence of feedback effects from banks to other financial institutions and from financial systems back to real economy still represent a major modelling shortcoming. This limitation implies that second round effects of the initial shock still tend to be ignored by the modellers. Central banks are extending their models with a feedback loop usually by using reduced form models, more specifically VAR models that include impulse responses. As mentioned, examples of such practices are illustrated in Espinoza & Prasad (2010), where the panel VAR analysis is conducted in order to examine nonperforming loans in GCC banking system and their macroeconomic effects (ECB, 2006, p. 86).

1.5.3 NON-LINEARITIES

Most of the stress test models implicitly assume constant statistical relationships among variables, which might not be the case in a stress situation. Mathematically this would mean that a three standard deviation shock is not simply just three time multiplication of a one standard deviation shock. Non-linearities can be a result of endogenous behavioural responses or they can occur due to misspecification of econometric models. Namely, most of the macroeconomic models impose a log-linear specification, which can also be interpreted as a Taylor approximation of mean outcome around the equilibrium. But clearly for the stress tests where tails of distribution are of interest this cannot hold. Therefore, other non-linear specifications such as probit have been introduced. Another possible solution would be re-estimating VAR models. A re-estimated model includes stressed values of variables of interest and can thus take potential changes in their correlations into account (Drehmann, 2008, p. 82; Foglia, 2008, p. 8).

However, Drehmann (2008, p. 83) argues that non-linearites may not represent such a problem after all, especially if the objective is communication. Accounting for non-linearities would not reveal any additional information about the transmissions from shocks to impacts. It would however change the levels of different stress scenarios, which may be important for the purpose of risk management.

1.5.4 DISTRIBUTION ASSUMPTIONS

In many cases unrealistic assumptions on distribution of risk factors have been made. Assuming normal distributions may considerably underestimate the severity and frequency of the stress events. Therefore it is important to assume non-normal distributions with fat tails, which result in a higher probability of stress events, for example once in fifty years instead of once in a hundred years if one considers the plausibility condition, explained earlier (Isogai, 2009).

2 STRESS-TESTING THE NON-FINANCIAL CORPORATE PORTFOLIOS FOR EURO AREA BANKING SYSTEMS

In this section I attempt to conduct a stress-testing exercise for selected euro area countries in order to demonstrate the application of the multi-step process scheme and other theoretical concepts described in the previous sections. For this reason I first construct adverse macroeconomic scenario based on some probability level, which results are latter linked to countries' loan performance data via the satellite model. Based on the obtained projections from the stress analysis, I try to determine whether euro area banking systems hold sufficient capital buffers necessary to withstand a potential macroeconomic stress event. Finally, the results obtained from the stress analysis are compared to the 2011 EU-wide stress test results.

2.1 METHODOLOGY AND DATA

The model used in the empirical exercise consists of a country-by-country analysis, where countries were selected based on the availability and length of time series data for write-offs, regarding the non-financial corporate loans. Another condition considered was an attempt to include both most affected countries by the latest crisis as well as the countries that are perceived to perform better. Therefore, countries selected for the analysis were the following: Italy, Portugal, Spain and Greece; which were compared to Belgium, Germany, Finland and France as the benchmark cases.

The model consists of two parts, where the first one is building macroeconomic scenarios, which are in the second part used to forecast future write-offs for non-financial corporate loans for a particular country.

2.1.1 MACROECONOMIC SHOCK SCENARIO

In order to estimate future adverse scenarios, we use the multivariate shock approach. The multivariate scenario analysis reflects the change in various macroeconomic variables and allows for their simultaneous interaction (Vukelić, 2011, p. 15).

As it was shown in the sub-section 1.4, most commonly used macroeconomic variables to describe credit risk are: GDP growth, unemployment, a short term interest rate, exports growth, domestic consumption, a stock index, and interest rate spread or a long term interest rate. For the purpose of this particular analysis the focus is on the first three. There are several reasons why other listed variables are omitted. The objective of the analysis is to focus on general scenarios or scenarios that affect countries in similar ways and are thus comparable. For example, some countries, i.e. smaller countries, are export oriented and some tend to rely more on domestic consumption, meaning that other variables (i.e. export growth) would capture country-specific characteristics that would not allow for objective comparison from the authority's point of view. Thus GDP growth and unemployment are chosen as more general macroeconomic variables than exports and domestic consumption. The reason for not using the interest rate spread variable or the long term interest rate variable is because the expectation about their behaviour is ambiguous. Some authors advocate that an increase of a long term interest rate represent an adverse shock, whereas papers from van den End et al. (2006, p. 4) and Carling, Jacobson, Linde and Roszbach (2002, p. 15) say that long term interest rates or interest spreads are negatively correlated to default rates. Their reasoning is that banks will be willing to renegotiate loans at a higher long term interest rate, given that banks borrow money at the short-term interest and lend it at a long-term interest. Similar ambiguous results or correlations we observed when I tried to conduct the model with those two variables. The reason for omitting stock index data is that GDP growth mimics the movement with lags, as it takes time for shock to transfer from the financial sector to the real economy (the analysis is based on corporate loans). Therefore lags demanded in linking equation (see section 2.1.3) reached very high number in already short window for write-offs data.

Expectations and behaviour for variables used in the model are the following (Lye, Loh, & Tan, 2002, p. 140):

Real GDP growth (in the analysis denoted as YER): Quarterly GDP data, transformed into year to year growths, has been used as a proxy for a business cycle in order to measure an overall activity of the economy. The GDP variable is expected to be negatively correlated with the write-offs, meaning that the higher the GDP growth the lower the write-offs rate.

Unemployment rate (denoted as URX): URX data indicates the state of aggregate savings and demand for investments and thus investment values. Positive correlation is expected, meaning that the higher the unemployment rate the higher the write-offs rate. Again quarterly data has been used.

A **short term interest rate (denoted as STN):** An increase in the short-term interest rate increases the likelihood of carrying amount to be higher than the recoverable amount, resulting in an increased need to write off the book value. In other words, increased short-term interest rates make the existing loans costlier, causing more delayed payments and higher write-offs rates. Again quarterly data has been used.

In order to perform the multivariate shock scenario for these three variables the basic vector-auto-regression model (VAR) is used:

$$macro_t = A_1 macro_{t-1} + \cdots + A_p macro_{t-p} + CD_t + u_t, \tag{1}$$

where $macro_t = (GDP_t, UR_t, STN_t)'$ is a vector of endogenous macroeconomic variables, D_t is the deterministic part of the equation, which may be comprised of a constant, linear trend, seasonal dummies and impulse dummies if necessary (see section 1.3), and u_t is unobservable zero mean white noise process. The A and the C are parameter matrices. Model is estimated with the generalized least square (GLS) method up to the fourth quarter of 2010. Once the model has been estimated and proper correlations between macro variables are established, these correlations are used to forecast future macro values. There are restrictions imposed on the model, such that only coefficients surpassing significance threshold of t-statistic 2.00 are allowed. The forecasts are computed recursively, based on the conditional expectations assuming independent white noise u_t:

$$macro_{t+1|t} = A_1 macro_t + \cdots + A_p macro_{t+1-p} + CD_{t+1} \tag{2}$$

$$macro_{t+1|t} = A_1(a_1 macro_{t-1} + \cdots + a_p macro_{t-p} + cd_t + e_t) + \cdots + A_p macro_{t+1-p} + CD_{t+1}$$

$$macro_{t+2|t} = A_1 macro_{t+1|t} + \cdots + A_p macro_{t+2-p} + CD_{t+2} \tag{3}$$

...

Forecasts are given for 8 quarters ahead, meaning that the last forecast is placed in the fourth quarter of 2012. In order to satisfy condition on the adverse shock being *″extreme but plausible″*, forecasts on 99 % bound on a confidence interval have been chosen. Assuming that disturbance factor u is normally distributed confidence interval for the case of GDP variable for one period ahead forecast can be written as:

$$[GDP_{t+1|t} \text{-} C_{1-\gamma/2}\sigma_{GDP}, GDP_{t+1|t} + C_{1-\gamma/2}\sigma_{GDP}], \quad (4)$$

where $C_{1-\gamma/2}$ is the (1-$\frac{\gamma}{2}$) 100 percentage point of the standard normal distribution and σ_{GDP} is the standard deviation of GDP. Because GDP is negatively correlated with write-offs, values on the lower bound of 99 % confidence interval have been chosen, whereas in case of unemployment and interest rate values on upper bound have been chosen. These values are then used to forecast future values of write-offs through the satellite model (Lutkepohl, Kratzig, & Boreiko, 2006, pp. 2-3; 37-38).

2.1.2 SATELLITE MODEL

In the second part macro variables are linked to write-offs data for nonfinancial corporate loans (WRO). The equation linking WRO and macro variables is combined with the autoregressive (AR) process, where macro variables enter equation as exogenous variables and WRO is the endogenous dependant autoregressive variable:

$$WRO_t = A_1 WRO_{t-1} + \cdots + A_p WRO_{t-p} + B_0 macro_t + \cdots + B_q macro_q + CD_t + u_t, \quad (5)$$

where $macro_t = (GDP_t, UR_t, STN_t)'$ is a vector of exogenous macroeconomic variables, D_t is the deterministic part of the equation, which may be comprised of a constant, linear trend, seasonal dummies and impulse dummies if necessary (see section 2.1.3), and $\mathrm{u_t}$ is unobservable zero mean white noise process. A, B and C are the parameter matrices. Again, model up to the fourth quarter of 2010 was estimated in order to establish correlations between macro variables and WROs. As in the macroeconomic model the significance threshold has been set to 2.00 value of t-statistics for coefficient. The obtained adverse macroeconomic forecasts from the macro scenario model are then added to these correlations to forecast the future write-off rates for each country separately. The forecast horizon depends on the exogenous lags required in the model. The purpose is that at least a one year window of stressed scenario is included. So in case where the model shows that WRO respond after four lags, the forecast horizon is 8 quarters (2 years), meaning that WRO forecast in 2012 Q4 includes macro stressed variables in 2011 Q4. Obviously if a model exhibits significant correlation with the exogenous macro variables in the first lag or at the present time, the stress in 2012 Q3 (2012 Q4 respectively) is also included (Lutkepohl, Kratzig, & Boreiko, 2006, p. 2).

2.1.3 MODEL ADEQUACY

This section describes the model checking procedure to ensure the adequacy of the model. All time series were tested for stationarity. Process is considered to be non-stationary if it contains a unit root. In other words, the moments of the process are time dependent. For illustration consider a simple first order autoregressive process:

$$y_t = \rho_1 y_{t-1} + \varepsilon_t, \tag{6}$$

with characteristic polynomial defined as $\alpha(L) = 1 - \rho L = 0$. The process has a unit root when ρ=1, so that the root of the polynomial z=1/ρ=1. In that case one can rewrite the process by iterative substitution, starting from $y_0 = 0$, so that:

$$y_t = y_0 + \sum_{j=1}^{t} \varepsilon_j \tag{7}$$

In that case the variance of the process takes form of $E({y_t}^2) = \sum_{j=1}^{t} \sigma^2 = t\sigma^2$, meaning that variance depends on t and it is diverging to infinity with t. To check for the potential unit roots present in the data the Augmented Dickey-Fuller Test was applied. The Dickey-Fuller test is applied to the following form of a model:

$$\Delta y_t = intercept + \beta t + \Phi y_{t-1} + \sum_{j=1}^{p-1} \alpha_j^* \Delta y_{t-j} + u_t, \tag{8}$$

where $\Phi = -\alpha(1)$ and $\alpha_j^* = -(\alpha_{j+1} + \cdots + \alpha_p)$. Restrictions on the deterministic parts of the equation can be imposed, which corresponds to modelling a random walk (intercept and β equal to 0) or a random walk with a drift (β=0). Once the model is estimated, the Dickey-Fuller test statistics ($DF_t = \widehat{\Phi}/SE(\widehat{\Phi})$) are recovered in order to test the null hypothesis $\Phi = 0$ against the alternative $\Phi < 0$. Values of the DF statistics smaller than critical values (negative) reject the null hypothesis and thus reject the presence of a unit root. Time series were properly transformed into first or second differences where a presence of the unit root was detected (Krätzig & Lütkepohl, 2004, pp. 11-12).

The order of the VAR process was determined through the use of 4 tests, which are either sequential or based on information criteria computation. The first variety tests whether maximum lags in a given set differ from zero. As the name states, the sequence of null hypotheses are tested in order to determine the proper lag order: H_0: $L_{p_{max}}$=0, H_0: $L_{p_{max-1}}$=0, etc., till the null hypothesis is rejected for the first time. Consequently, the choice upon p_{max} is of a great significance, since picking maximum lag too high might cause rejections of the null hypothesis to early, whereas in the opposite case the optimal order might not be found due to the too short set. In general, choosing maximum lag too small tends to be less problematic since potential flaws arising from it will be revealed in model checking. Alternatively the information criteria computation is based on testing the goodness of fit, based on minimizing residual variance-covariance term and penalty term:

$$C(m) = logdet(\textstyle\sum_m) + C_T \varphi(m), \tag{9}$$

where $\sum_m = T^{-1} \sum_{t=1}^{T} \hat{u}_t \hat{u}_t'$ is the term estimating residual variance-covariance for the model of order m, $\varphi(m)$ is function that penalizes the large VAR orders, and C_T is the sequence that identifies a specific criterion (namely there are three criteria: the Akiake criterion, the Hannan and Quinn criterion, and the Shwarz criterion). When the sum of the two terms is at the minimum, the lag order is determined. The rule for choosing the proper lag from all tests run was to pick the lag number that majority of tests exhibited. When results were different for all tests, all possibilities were tried starting with the smallest one and stopping where the residual analysis showed least deficiency. In the case of the linking satellite equation, first exogenous lags had been determined to the point of the last significant lag and after that tests for endogenous lags were applied (Lütkepohl, 2007, pp. 22-25).

As far as the residual analysis is concerned the model was checked for autocorrelation and non-normality. For the purpose of the autocorrelation the Breusch-Godfrey LM test was applied. The test verifies whether residuals follow the autoregressive process of form:

$$u_t = \rho_1 u_{t-1} + \rho_2 u_{t-2} + \cdots + \rho_p u_{t-p} + e_t, \tag{10}$$

meaning that past errors influence the size of the error in the current period. The null hypothesis tested is therefore H_0: $\rho_1 \ldots \rho_p = 0$, against the alternative, stating that at least one of the parameters is statistically different from zero. The Breusch-Godfrey test statistics is constructed with estimates of the residuals e_t of the above autoregressive process and are obtained from the following auxiliary VAR model:

$$\widehat{u_t} = \alpha_1 y_{t-1} + \cdots + \alpha_p y_{t-p} + \rho_1 \hat{u}_{t-1} + \cdots + \rho_p \hat{u}_{t-p} + e_t \tag{11}$$

The Breusch-Godfrey LM statistics then takes the following form:

$$LM = T(K - tr(\widetilde{\textstyle\sum_R^{-1}} \widetilde{\textstyle\sum_e})) \sim X^2, \tag{12}$$

where $\widetilde{\sum_e} = 1/T \sum_{t=1}^{T} \widehat{e_t} \widehat{e_t'}$ is the residual covariance matrix estimator obtained from the full auxiliary model, whereas $\widetilde{\sum_R} = 1/T \sum_{t=1}^{T} \widehat{e_t^R} \widehat{e_t^{R\prime}}$ is the residual covariance matrix estimator obtained from a restricted auxiliary model, where $\rho_1 \ldots \rho_p = 0$. The statistics is proven to follow the asymptotic distribution X^2. Autocorrelation problem was treated where needed by increasing endogenous lags (Lütkepohl, 2007, pp. 27-28).

The process was also tested for potential deviation from normality assumptions. In other words, third moment was examined for potential asymmetries in distribution (skewness) as well as the fourth moment for potential fat tails of distribution (excessive kurtosis). Normality condition is not necessary for the estimation of the model, but it indicates room for improvement. The intuition behind normality tests is to decompose residual vectors into independent components and then check the compatibility of the third and fourth moments with those of normal distribution. The first step is to compute the residual covariance matrix:

$$\widetilde{\textstyle\sum_u} = T^{-1} \sum_{t=1}^{T} \hat{u}_t \, \hat{u}_t', \tag{13}$$

from which the standardized residuals can be computed as $\hat{u}_t^s = (\hat{u}_{1t}^s \dots \hat{u}_{Kt}^s)' = \widetilde{\sum_u}^{-1/2} \hat{u}_t$, where $\widetilde{\sum_u}^{-1/2} = \sigma$. By using standardized residuals, the third moment (skewness) can be defined as:

$$\mathbf{b_1} = (b_{11}, \dots, b_{1\mathrm{K}})' \quad \text{with} \quad b_{1k} = T^{-1} \sum_{t=1}^{T} (\hat{u}_{kt}^s)^3, \tag{14}$$

and fourth moment (kurtosis) as equation (15):

$$\mathbf{b_2} = (b_{21}, \dots, b_{2\mathrm{K}})' \quad \text{with} \quad b_{2k} = T^{-1} \sum_{t=1}^{T} (\hat{u}_{kt}^s)^4. \tag{15}$$

From this, the Jarque-Bera test for normality can be defined as:

$$JB = \frac{T}{6}\left(S^2 + \frac{1}{4}K^2\right), \tag{16}$$

where S^2 is the test statistics for skewness defined as $S^2 = \mathbf{b_1}'\mathbf{b_1}$ and K^2 is a test statistics for the excessive kurtosis defined as $K^2 = (\mathbf{b_2} - 3_{\mathrm{K}})'(\mathbf{b_2} - 3_{\mathrm{K}})$. Vector $3_{\mathrm{K}} = (3, \dots, 3)'$ which dimensions are (K × 1) is a correction term that makes normal distribution kurtosis 0. This means that normal distribution samples have value of skewness equal to 0 and value of the excessive kurtosis equal to 0 (value of kurtosis equal to 3). Larger JB statistics implies larger deviations from the normal distribution. In cases where non-normalities were detected, impulse dummies were applied in order to encompass excessive extreme deviations (values of standard residuals larger than three standard deviations). Extreme deviations and thus dummy value of 1 was determined based on the residual plots. The rule was not to allow for more than 1 % of such observation (Lütkepohl, 2007, pp. 29).

2.2 COUNTRY-BY-COUNTRY ANALYSIS

In this section a detailed model analysis for each individual country is presented. Country-by-country analyses include descriptions of macro variables, macroeconomic shocks and linking equations used in the write-off forecasts. In addition to that, the explanations of the obtained results at the end of each case are offered. Country codes have been added to the variables' notations, for example variables for Italian case are denoted as YER_IT (GDP growth rate), URX_IT (unemployment rate) and STN_IT (short-term interest rate).

2.2.1 ITALY

Macro model window ranges according to the shortest time series (STN_IT), from 1993 Q1 to 2010 Q4. In the estimation of the satellite model with write-offs data for Italy (WRO_NFC_IT), the exogenous AR process is ranging from 1999 Q2 to 2010 Q4.

2.2.1.1 ITALY-MACRO SCENARIO ANALYSIS

The macro VAR model for the scenario analysis was initially based on 4 endogenous lags, suggested by 2 out of 4 info criteria. However, model exhibited non-normality as the residual analysis showed presence of both skewness and kurtosis. Therefore, an additional impulse dummy was imposed, undertaking value 1 in 2008 Q4, since the standard residual relating to the variable STN_IT exceeded 3 standard deviation criteria in this year. Deterministic part of the model also included trend and intercept. Non-normality was efficiently removed and diagnostic test did not show any signs of autocorrelation. Macro model was based on first differences, due to non-stationarity of the URX_IT and STN_IT variables. Extreme but plausible 99% bound un-differenced macro forecasts are presented in the following table:

Table 2: Forecast for Italy's worst-case macro scenario

Time	YER_IT	STN_IT	URX_IT
2011Q1	-0,3282	1,6994	8,5998
2011Q2	-1,9555	2,2201	8,8010
2011Q3	-3,4326	2,6616	9,0821
2011Q4	-4,3302	3,0395	9,3959
2012Q1	-4,3784	3,3693	9,8036
2012Q2	-4,3223	3,6625	10,1472
2012Q3	-4,1417	3,9279	10,4624
2012Q4	-4,0933	4,1713	10,7277

The model predicts a 4.4 percent decline in GDP in first period of 2012 which is predicted to fully materialize in unemployment rate and short-term rate, when peaks at 4.2 percent and 10.7 percent, respectively, are reached.

2.2.1.2 ITALY-SATELLITE MODEL

Linking process for the Italian case is based on 4 exogenous and 2 endogenous lags. In the deterministic part of the model, intercept and trend are included as they both indicate a significant correlation. Variables URX_IT and STN_IT are the only variables set to the first difference as they exhibit non-stationarity. The model did not show any signs of autocorrelation, non-normality or instability. The restricted AR model with exogenous macro variables and endogenous write-offs variable is presented in the following table.

Table 3: The restricted satellite model for Italy, with write-offs as the endogenous variable and exogenous macro variables

Lags	WRO_NFC_IT	STN_IT_d1	URX_IT_d1	YER_IT
t	/			
t-1	1,313***			
t-2	-0,471***	0,257***	0,088***	
t-3				
t-4			0,065**	

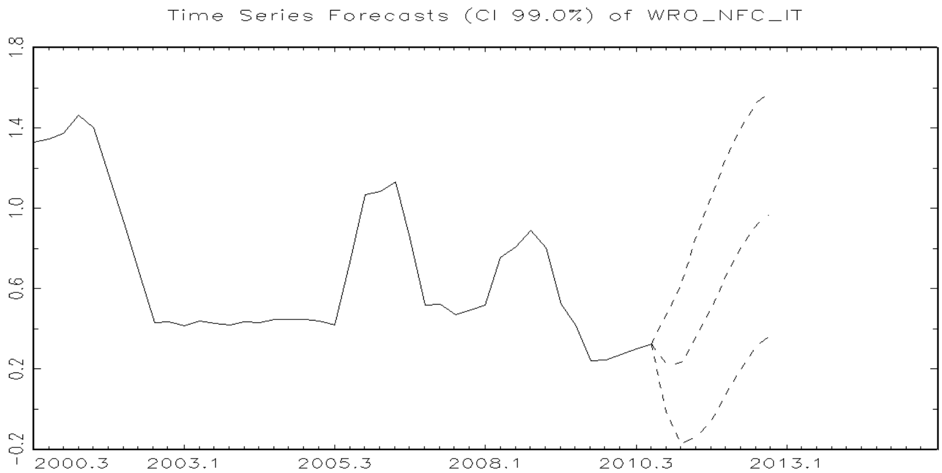
*Note: *** - significant at 1 %, ** - significant at 5 %*

As it can be seen from the table, all exogenous macro variables behave according to the initial expectations, meaning that variables STN_IT and URX_IT exhibit a positive correlation with write-offs. However the model shows no significant correlation with GDP growth. These correlations, along with the macro forecast, are used to forecast future write-offs. 8 quarter forecasts were produced so that at least 4 quarters of adverse macro forecasts are used (2011 Q4) as the URX_FI shows correlation with 4 lags.

Table 4: Write-offs forecast for Italy with 99% upper and lower confidence levels

Time	**Forecast**	**Lower CI**	**Upper CI**
2011Q1	0,2274	-0,0143	0,4691
2011Q2	0,2239	-0,1751	0,6230
2011Q3	0,3630	-0,1381	0,8641
2011Q4	0,5022	-0,0571	1,0614
2012Q1	0,6669	0,0784	1,2554
2012Q2	0,8052	0,2038	1,4066
2012Q3	0,9200	0,3139	1,5262
2012Q4	0,9779	0,3703	1,5855

Figure 3: Write-offs forecast for Italy with 99% upper and lower confidence levels



Prior the estimation of the model, the Italian write-offs stabilized at around 0.3 %. Obtained forecast predict a slight decrease in the first two periods (2011 Q1 and 2011 Q2). Although this is not aligned with assumptions it is expected since the model shows that first shock enters the model with 2 lags, meaning that it is first considered in 2011 Q3. The URX_IT variable affects the write-offs with a 4 lags delay. However, the unemployment rate persists at a relatively high level even in the year before shock, explaining why the decrease does not persist for the whole 4 quarter period until constructed shocks are incorporated. Therefore, after 2011 Q2 a steep increase explained by the model can be observed.

Forecasts for Italy are therefore predicting a peak impact close to 1 % in the final forecasted period.

2.2.2 PORTUGAL

Macro model window ranges according to the shortest time series (YER_PT), from 1996 Q2 to 2010 Q4. In estimation of the linking equation the write-offs data for Portugal (WRO_NFC_PT) were used, which determines the range of exogenous AR model to be from 1999 Q3 to 2010 Q4.

2.2.2.1 PORTUGAL-MACRO SCENARIO ANALYSIS

The macro VAR model for the scenario analysis was initially based on 1 endogenous lag, suggested by 4 out of 4 info criteria. However, there were signs of non-normality in the model, which was dealt with by adding an impulse dummy, switching to 1 in 2008 Q4, where standard residual value for variable STN_PT exceeded 3 standard deviation rule described in the methodology. Residual analysis further indicated the presence of autocorrelation. In order to properly deal with autocorrelation the number of lags was increased to 4. The deterministic part in the model includes intercept, but excludes trend due to the insignificance of the latter. Non-normality was efficiently removed and diagnostic test did not show any signs of autocorrelation. Macro model is based on first differences due to non-stationarity of all variables. Extreme but plausible 99% bound un-differenced macro forecasts are presented in the following table:

Table 5: Forecast for Portugal's worst-case macro scenario

Time	YER_FI	STN_FI	URX_FI
2011Q1	-1,8213	1,7254	13,2691
2011Q2	-2,5514	2,3380	13,8664
2011Q3	-3,2516	2,8684	14,5054
2011Q4	-3,7001	3,3282	15,0904
2012Q1	-3,5778	3,7319	15,6445
2012Q2	-3,8139	4,0921	16,1587
2012Q3	-4,0171	4,4183	16,6391
2012Q4	-4,2126	4,7175	17,0876

The model predicts the peak of adverse scenario in the last quarter of the forecast, where a 4.2 percent decline in GDP is predicted, short-term interest rate reach 4.7 percent, and the unemployment rate is predicted to be around 17 percent.

2.2.2.2 PORTUGAL-SATELLITE MODEL

The linking process in the Portugal case exhibited 7 exogenous lags and based on that the information criteria computation suggested 8 endogenous lags. In the deterministic part of the model only intercept is included as it is the only one to indicate a significant correlation.

All variables, including WRO_NFC_PT, are set to first difference due to their non-stationarity. The model did not show any signs of autocorrelation, non-normality or instability. The restricted AR model with exogenous macro variables and endogenous write-offs variable is presented in the following table.

Table 6: The restricted satellite model for Portugal, with write-offs as endogenous variable and exogenous macro variables

Lags	WRO_NFC_PT_d1	STN_PT_d1	URX_PT_d1	YER_PT_d1
t	/	0,037***		-0,056***
t-1			0,770***	
t-2				
t-3	0,602**	-0,061***	0,165***	0,050***
t-4	-0,304***	0,063***		
t-5		0,045***	0,109***	-0,039***
t-6	-0,191**	0,126***	0,138***	-0,054***
t-7		0,052***		
t-8	0,487***			

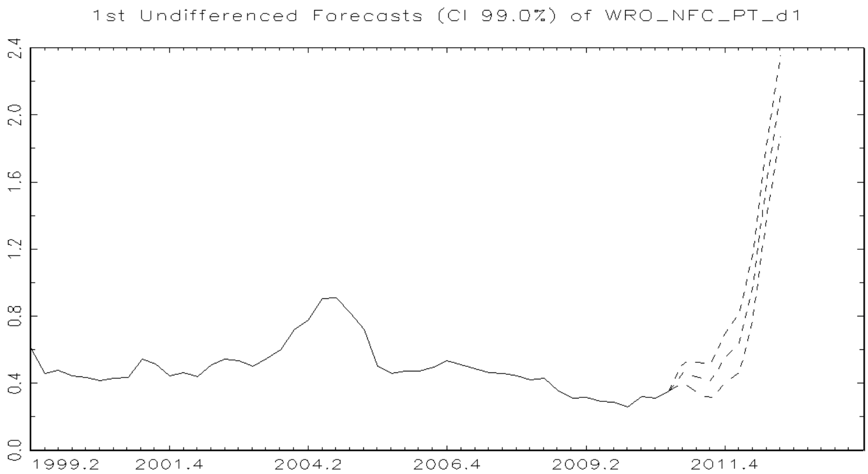
*Note: *** - significant at 1 %, ** - significant at 5 %*

A combined effect of variables through all lags is expected. Variables STN_PT and URX_PT are all in all positively correlated to write-offs, whereas YER_PT is in the summed effect negatively correlated to write-offs. These correlations along with the macro forecast are then used to forecast future 8 horizon write-offs. Results of the forecast are presented in the following table:

Table 7: Write-offs forecast for with 99% upper and lower confidence levels

Time	Forecast	Lower CI	Upper CI
2011Q1	0,4659	0,4033	0,5285
2011Q2	0,4329	0,3443	0,5215
2011Q3	0,4116	0,3031	0,5201
2011Q4	0,5489	0,4012	0,6967
2012Q1	0,6335	0,4549	0,8121
2012Q2	0,9662	0,7700	1,1624
2012Q3	1,6018	1,3851	1,8185
2012Q4	2,1227	1,8872	2,3581

Figure 4: Write-offs forecast for Portugal with 99 % upper and lower confidence levels



The chart above shows growth of write-offs through a major part of the forecasted horizon. In the first year of the forecast the growth is a bit slower, which can be explained by 7 exogenous lags that indicate incorporation of data from 2009. Namely, the general improvement in condition of lending (STN_PT was decreasing in 2009 and in first half of 2010) held write-offs from growing as rapid in 2011 as they were forecasted to grow in 2012. The write-offs, according to the obtained estimation, are going to reach the peak in 2012 Q4 at around 2.1 %.

2.2.3 FINLAND

The macro model window ranges according to the shortest time series (STN_FI), from 1992 Q2 to 2010 Q4. In estimation of the linking equation, where write-offs data are used (WRO_NFC_FI), the exogenous AR model is ranging from 1999 Q2 to 2010 Q4.

2.2.3.1 FINLAND-MACRO SCENARIO ANALYSIS

The macro VAR model for the scenario analysis was initially based on 6 endogenous lags, suggested by 2 out of 4 info criteria. However, model exhibited non-normality as the residual analysis showed presence of both skewness and kurtosis. Therefore an additional impulse dummy was employed, undertaking value 1 in 2008 Q4 and 2005 Q4 as the standard residual value of the variable STN_FI exceeded 3 standard deviation criteria in these periods. The deterministic part in the model also included trend and intercept. Non-normality was efficiently removed and the diagnostic test did not show any signs of autocorrelation. The macro model was based on first differences, due to non-stationarity of the YER_FI variable. Extreme but plausible 99% bound un-differenced macro forecasts are presented in the following table:

Table 8: Forecast for Finland's worst-case macro scenario

Time	YER_FI	STN_FI	URX_FI
2011Q1	0,0048	1,7244	8,1147
2011Q2	-2,9925	2,2294	8,3285
2011Q3	-4,0593	2,6472	8,7117
2011Q4	-5,7664	2,9863	9,1123
2012Q1	-5,5829	3,2725	9,5155
2012Q2	-5,4242	3,5229	9,9123
2012Q3	-5,3885	3,7295	10,1947
2012Q4	-5,2540	3,9083	10,3673

The harshest decline in GDP (5.7 percent) is expected by the end of 2011, whereas the short-term interest rate and unemployment rate reache their peaks with one year lag by the end of 2012.

2.2.3.2 FINLAND-STELLITE MODEL

Linking process for the Finish case is based on 4 exogenous and 3 endogenous lags. In the deterministic part of the model, intercept and trend are included as they both indicate a significant correlation. This time the only variable set to first difference was the YER_FI as it is the only variable that exhibits non-stationarity and, unlike in macro case, it enters the model as exogenous variable. The model did not show any signs of autocorrelation, non-normality or instability. The restricted AR model with exogenous macro variables and endogenous write-offs variable is presented in the following table:

Table 9: The restricted satellite model for Finland, with write-offs as endogenous variable and exogenous macro variables

Lags	WRO_NFC_FI	STN_FI	URX_FI	YER_FI_d1
t	/			
t-1	0,935***			-0,025***
t-2		0,036***		
t-3	-0,314**			
t-4			0,163***	

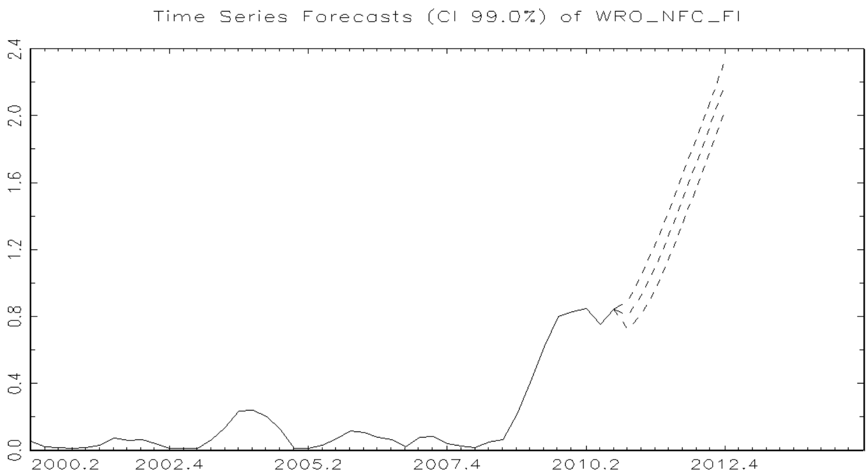
*Note: *** - significant at 1 %, ** - significant at 5 %*

As it can be seen from the table, all exogenous macro variables behave according to initial expectations, meaning that variables STN_FI and URX_FI exhibit a positive correlation with write-offs, whereas YER_FI exhibits a negative correlation. These correlations along with a macro forecast are then used to forecast future write-offs. The model was set to produce 8 quarter forecast in order to capture at least 4 period forecasted macro shocks (2011 Q4) as the URX_FI shows a correlation with 4 lags.

Table 10: Write-offs forecast for Finland with 99% upper and lower confidence levels

Time	Forecast	Lower CI	Upper CI
2011Q1	0,8063	0,7214	0,8911
2011Q2	0,9298	0,8137	1,0460
2011Q3	1,0963	0,9585	1,2342
2011Q4	1,2911	0,1468	1,4354
2012Q1	1,5150	1,3700	1,6601
2012Q2	1,7302	1,5848	1,8756
2012Q3	1,9545	1,8075	1,1016
2012Q4	2,1830	2,0337	2,3322

Figure 5: Write-offs forecast for Finland with 99% upper and lower confidence levels



On the chart above a rapid increase of the Finish write-offs can be observed, stabilizing at around 0.8 % prior to the estimation of the future write-offs. A slight decrease in the first period (2011 Q1) is demonstrated. However, this is the period where none of the macro shocks enter the linking process and according to data in 2010 (except for the URX_FI) the general climate in the Finish economy started to improve. Namely, the Finish write-offs need one lag to respond to at least one of the shocks, which in that case would be YER_FI. The reason why this decrease lasts for only one period, where unemployment rate affects write-offs after 4 lags, is that unemployment in Finland rose significantly in 2009 Q3 and persisted at a high level (around 8.2 %) until 2010 Q4, meaning that URX_FI did not contribute to improvement of the general climate in 2010. Therefore, already after 2011 Q1 a steep increase can be observed, when macro predictions are incorporated in the model. Considering all that, it is expected that write-offs for Finland are going to reach the peak at around 2.2 % in 2012 Q4.

2.2.4 SPAIN

The macro model window ranges according to the shortest time series (YER_ES), from 1996 Q1 to 2010 Q4. In estimation of the linking equation the write-offs data for Spain (WRO_NFC_ES) were incorporated as the shortest time series, meaning that exogenous AR model is ranging from 1999 Q2 to 2010 Q4.

2.2.4.1 SPAIN-MACRO SCENARIO ANALYSIS

The macro VAR model for the scenario analysis was initially based on 5 endogenous lags, suggested by 3 out of 4 info criteria. System testing procedure excluded trend and intercept as statistically insignificant variables. However, the non-normality test reported skewness and kurtosis. Therefore, an additional impulse dummy was introduced, undertaking value 1 in 2008 Q4 in which the standard residual value of the variable STN_ES exceeded 3 standard deviation criteria in this year. A new model with a dummy variable was based on 4 endogenous lags, suggested by the Hannan-Quinn and Schwarz info criteria, excluding trend and intercept. Non-normality was efficiently removed and diagnostic test did not show any signs of autocorrelation. Extreme but plausible forecasts based on 99% bound on a confidence level are presented in the following table.

Table 11: Forecast for Spain's worst-case macro scenario

Time	YER_ES	STN_ES	URX_ES
2011Q1	-0,5791	1,6756	21,2
2011Q2	-2,5199	2,4304	22,0
2011Q3	-3,8603	3,0335	23,0
2011Q4	-5,6145	3,4955	24,2
2012Q1	-7,0057	3,9540	25,4
2012Q2	-7,3014	4,4211	26,7
2012Q3	-7,6660	4,9255	28,0
2012Q4	-7,6801	5,5453	29,3

The adverse macroeconomic scenario reaches the peak by the end of the forecasted horizon. The GDP is expected to drop by 7.7 %, short-term interest rate ought to increase to 5.5 percent, and unemployment rate is forecasted to reach 29 % by this extreme but plausible prediction.

2.2.4.2 SPAIN-SATELLITE MODEL

All the variables, including write-offs were found to be non-stationary. Consequently, all the variables were transformed to their first differences and proven to be stationary. The linking equation for the Spanish case is based on 6 exogenous and 2 endogenous lags. The latter was suggested by all info criteria, while intercept and trend were found to be statistically insignificant and were therefore excluded from the model. The model did not show any signs of autocorrelation, non-normality or instability. The restricted AR model with exogenous macro variables and an endogenous write-offs variable is presented in the following table.

Table 12: The restricted satellite model for Spain, with write-offs endogenous variable and exogenous macro variables

Lags	WRO_NFC_ES_d1	STN_ES_d1	URX_ES_d1	YER_ES_d1
t	/			-0,021***
t-1	0,781***	0,19***		0,022***
t-2	-0,480***			-0,026***
t-3				
t-4				
t-5				-0,013**
t-6			0,034***	

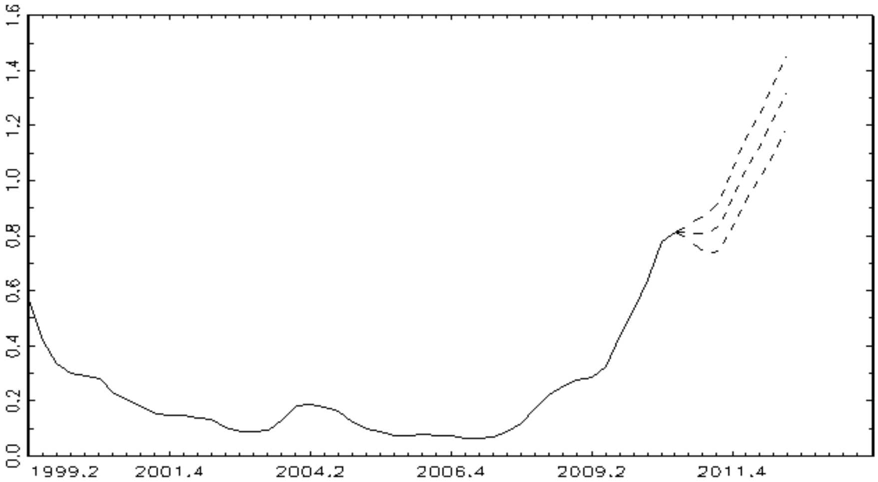
*Note: *** - significant at 1 %, ** - significant at 5 %*

According to the upper table, all exogenous macro variables in summation behave according to the initial expectations, meaning that variables STN_ES and URX_ES exhibit positive correlation with write-offs, whereas YER_ES exhibits a negative correlation. Considering the estimated coefficients listed in the upper table the 8 horizon forecast for write-offs was produced, using forecasted values of exogenous variables from the adverse macroeconomic scenario. The results are presented in the table below.

Table 13: Write-offs forecast for Spain with 99% upper and lower confidence levels

Time	Forecast	Lower CI	Upper CI
2011Q1	0,8119	0,7799	0,8439
2011Q2	0,8062	0,7408	0,8715
2011Q3	0,8269	0,7374	0,9165
2011Q4	0,9347	0,8309	1,0384
2012Q1	1,0472	0,9346	1,1597
2012Q2	1,1278	1,0081	1,2476
2012Q3	1,2337	1,1065	1,3610
2012Q4	1,3332	1,1979	1,4685

Figure 6: Write-offs forecast for Spain with 99% upper and lower confidence levels



According to the chart above we can see that a rapid increase in write-offs prior to the forecasting period gradually stops at around 0.8 %. This is due to the improvement of general macroeconomic environment after the crisis in 2008. Furthermore, forecasts predict that write-offs remain stable at around 0.8 % for the first two quarters until the negative macro scenario comes into effect. After 2011 Q2 the write-offs rate starts to increase significantly. This happens because the write-offs rate needs time to respond to negative macroeconomic conditions. Namely, the coefficient for GDP growth in t-1 exhibits a positive correlation (0.022), which means that reduced GDP by 1 percent contributes to 0.022 percentage point lower level of the write-offs rate. This, however, changes after two lags. Moreover the coefficient (0.034) with the largest impact that relates unemployment to the write-offs level comes with a lag of 6 periods, which means that high unemployment does not affect write-offs before 2012 Q2. Altogether it is expected that write-off levels for Spain will just exceed 1.3 % in the final forecasting period.

2.2.5 FRANCE

The macro model window ranges according to the shortest time series (YER_FR), from 1991 Q1 to 2010 Q4. In estimation of the linking equation the write-offs data for France (WRO_NFC_ES) were incorporated as the shortest time series, meaning that exogenous AR model is ranging from 1999 Q2 to 2010 Q4.

2.2.5.1 FRANCE-MACRO SCENARIO ANALYSIS

The macro VAR model for the scenario analysis was initially based on 4 endogenous lags, suggested by Final Prediction Error. However, the non-normality test reported skewness and kurtosis. Therefore an additional impulse dummy was introduces undertaking value 1 in 2008 Q4, as the standard residual relating to the variable STN_FR exceeded 3 standard deviation criteria in this year. The deterministic part in the model also includes trend and intercept. A new model with a dummy variable was also based on 4 endogenous lags, suggested by the same criterion as before. Non-normality was efficiently removed and a diagnostic test did not show any signs of autocorrelation. Extreme but plausible forecasts, based on 99% bound on a confidence level are presented in the following table.

Table 14: Forecast for France's worst-case macro scenario

Time	YER_FR	STN_FR	URX_FR
2011Q1	-0,5009	2,1217	9,9838
2011Q2	-1,3989	2,5343	10,3523
2011Q3	-2,0358	2,8057	10,7096
2011Q4	-2,5263	3,0781	11,1038
2012Q1	-2,4396	3,3269	11,5000
2012Q2	-2,3079	3,5696	11,7946
2012Q3	-2,2373	3,8114	12,0219
2012Q4	-2,2718	4,0313	12,2035

The adverse macroeconomic scenario is expected to hit the bottom by the end of the 2012, when GDP growth is expected to be -2.3 %, short-term interest rate 4 % and unemployment rate 12.2 %.

2.2.5.2 FRANCE-SATELLITE MODEL

All the variables, including write-offs rate were found to be non-stationary. Consequently all the variables were transformed to its first differences. The linking process for the French case is based on 6 exogenous and 5 endogenous lags. The latter was suggested by all info criteria while trend was excluded from the deterministic part as it was found to be statistically insignificant. The model did not show any signs of autocorrelation or instability, however, non-normality test was not able to reject presence of skewness. This means that bias results cannot be denied. The restricted AR model with exogenous macro variables and an endogenous write-offs variable is presented in the following table.

Table 15: The restricted satellite model for France, with write-offs as endogenous variable and exogenous macro variables

Lags	WRO_NFC_FR_d1	STN_FR_d1	URX_FR_d1	YER_FR_d1
t	/	0,014**	0,042***	
t-1	0,712***			
t-2		0,025***	-0,036***	-0,023***
t-3				
t-4	-0,772***		0,035***	
t-5	0,046***			
t-6				-0,028***

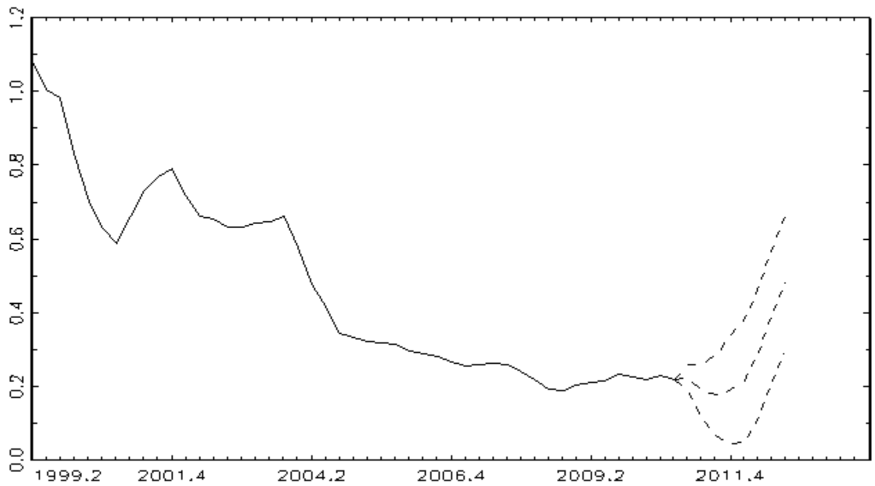
*Note: *** - significant at 1 %, ** - significant at 5 %*

According to the upper table, all exogenous macro variables in summation behave according to the expectations, meaning that variables STN_FR and URX_FR exhibit a positive correlation with write-offs, whereas YER_FR exhibits a negative correlation. Considering the estimated coefficients listed in the upper table an 8 horizon forecast for write-offs was produced, using forecasted values from the macroeconomic scenario. The results are presented in the table below.

Table 16: Write-offs forecast for France with 99% upper and lower confidence levels

Time	Forecast	Lower CI	Upper CI
2011Q1	0,2205	0,1831	0,2578
2011Q2	0,1874	0,1133	0,2614
2011Q3	0,1738	0,0626	0,2850
2011Q4	0,1882	0,0410	0,3354
2012Q1	0,2153	0,0491	0,3815
2012Q2	0,2894	0,1133	0,4654
2012Q3	0,3969	0,2162	0,5775
2012Q4	0,4879	0,3054	0,6704

Figure 7: Write-offs forecast for France with 99% upper and lower confidence levels



Write-off levels for French banking sector remained fairly stable throughout the crisis, despite the adverse economic situation in 2008 and 2009 when GDP went down by 3 % and unemployment went up from 7.6 % just to reach the double figures (10 %). When the shock was introduced in 2011 Q1 write-offs needed some time to respond since 5 out of 7 coefficients of exogenous variables lag at least 2 periods. So at first (2011 Q2 and 2011 Q3) write-offs decrease since some of the coefficients still take into account macro conditions before the shock. For example the GDP growth affects the write-off levels with 6 quarters lag, which means that the worst-case scenario is not fully taken into account before 2012 Q3, when the increase in write-off levels is the highest considering the whole forecasting period. Altogether, write-offs in French banking sector increase by more than two fold from 0.2185 % (2010 Q4) to 0.4879 % (2012 Q4). It seems that the French banking sector remains stable despite the negative macro shock. This can be attributed to a sound financial sector, low credit exposure, and the fact that the negative macro scenario was not as severe as in some other countries analyzed in the paper.

2.2.6 GERMANY

The macro model window ranges according to the shortest time series (YER_DE), which is from 1992 Q2 to 2010 Q4. In the estimation of the linking equation the write-offs data for Germany (WRO_NFC_DE) represent the shortest time series, meaning that exogenous AR model is ranging from 2003 Q4 to 2010 Q4.

2.2.6.1 GERMANY-MACRO SCENARIO ANALYSIS

The macro VAR model for the scenario analysis was based on 4 endogenous lags, suggested by 3 out of 4 information criteria for the optimal number of lags. The non-normality test reported both skewness and kurtosis. This was dealt with by adding an impulse dummy, switching to 1 in 2008 Q4, where the standard residual value for variable STN_DE exceeded 3 standard deviation rule described in the methodology. The deterministic part in the model also included intercept, but excluded trend due to the insignificance of the latter. A new model with a dummy variable was also based on 4 endogenous lags as suggested by the same 3 out of 4 info criteria. Non-normality was efficiently removed and the diagnostic test did not show any signs of autocorrelation. Extreme but plausible forecasts, based on 99% bound on a confidence level are presented in the following table.

Table 17: Forecast for Germany's worst-case macro scenario

Time	YER_DE	STN_DE	URX_DE
2011Q1	-0,2717	1,7162	6,9
2011Q2	-2,4541	2,2241	7,3
2011Q3	-3,6382	2,5596	7,7
2011Q4	-4,6537	2,8623	8,2
2012Q1	-4,1785	3,1609	8,6
2012Q2	-3,9355	3,4454	9,0
2012Q3	-3,8657	3,7427	9,3
2012Q4	-3,7853	4,0097	9,6

The worst drop in the German GDP was predicted for the last quarter of 2011, which fully materialized in unemployment rate and short-term interest rate by the end of 2012 when figures 9.6 % and 4 % are reached.

2.6.2 FRANCE-SATELLITE MODEL

All the variables were found to be non-stationary. Consequently, all the variables were transformed to their first differences. The linking equation for the German case is based on 4 exogenous and 3 endogenous lags. The optimal number of endogenous lags was suggested by 3 out of 4 info criteria. In the deterministic part of the model both intercept and trend were included since they exhibited a significant correlation. The model did not show any signs of autocorrelation, non-normality or instability. The restricted AR model with exogenous macro variables and an endogenous write-offs variable is presented in the following table.

Table 18: The restricted satellite model for Germany, with write-offs as endogenous variable and exogenous macro variables

Lags	WRO_NFC_DE_d1	STN_DE_d1	URX_DE_d1	YER_DE_d1
t	/	-0,026**		
t-1	-0,523***		0,077**	
t-2				
t-3		0,041**	0,245***	-0,026***
t-4		0,065***		-0,022***

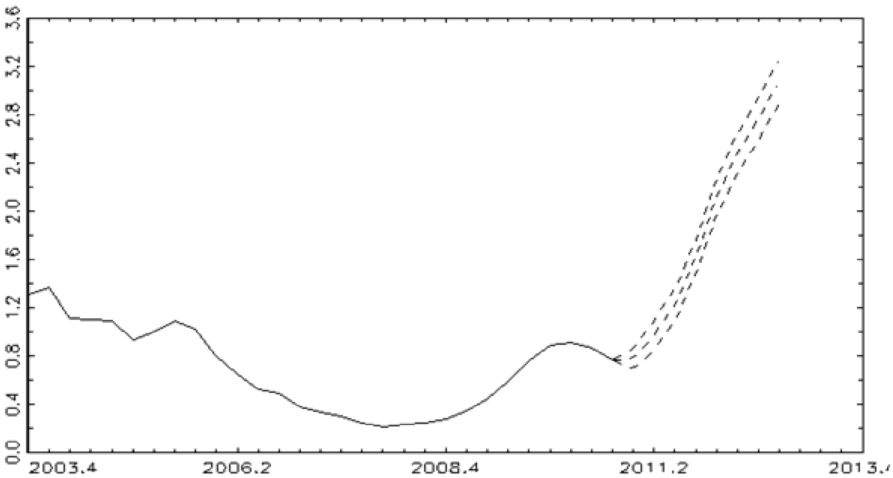
*Note: *** - significant at 1 %, ** - significant at 5 %*

Aggregate effect of all variables through all lags is expected, meaning that variables STN_DE and URX_DE exhibit a positive correlation with write-offs, whereas YER_DE exhibits a negative correlation. Considering the estimated coefficients listed in the upper table an 8 horizon forecast was produced, considering shocks in macroeconomic variables. The results are presented in the Table 19.

Table 19: Write-offs forecast for Germany with 99% upper and lower confidence levels

Time	Forecast	Lower CI	Upper CI
2011Q1	0,7719	0,6843	0,8596
2011Q2	0,9745	0,8505	1,0985
2011Q3	1,2258	1,0950	1,3567
2011Q4	1,6194	1,4820	1,7568
2012Q1	2,1152	1,9629	2,2675
2012Q2	2,4835	2,3176	2,6494
2012Q3	2,7728	2,5986	2,9471
2012Q4	3,0897	2,9075	3,2719

Figure 8: Write-offs forecast for Germany with 99% upper and lower confidence levels



The German economy performed extremely well in 2010. Its unemployment dropped by 1 percentage point and its GDP increased by 4 %. These positive macroeconomic indicators account for the improvement in terms of the write-offs rate before the forecasting period. However, with the introduction of macro shock the picture changes significantly. Like in most other cases the negative scenario needs some time to “kick in” since 5 out of 7 exogenous coefficients lag more than 2 periods. But after first two quarters write-offs start to increase immensely, stopping at approximately 3.1 % in 2012 Q4. The obtained results are showing high connectedness of the German credit default rates and the general macroeconomic situation. This would imply that bank lending represents the main source of funding for German companies and thus high exposure of the banking sector towards the non-financial sector. However this relationship was established by using short time series data reflecting sound economic times. The predictions obtained are linear and continuing also for the adverse situation produced by the model, which may be a bit unrealistic to expect.

2.2.7 BELGIUM

The macro model window ranges according to the shortest time series (YER_BE), from 1996 Q1 to 2010 Q4. In estimation of the linking equation the shortest time-series is the write-offs data for Belgium (WRO_NFC_BE), meaning that exogenous AR model is ranging from 2003 Q1 to 2010 Q4.

2.2.7.1 BELGIUM-MACRO SCENARIO ANALYSIS

The macro VAR model for the scenario analysis was initially based on 1 endogenous lag, suggested by the Schwarz Criterion. The System Testing Procedure excluded trend and intercept as statistically insignificant variables from the model. In addition to that, all of the chosen variables were non-stationary and thus transformed into first differences. The model exhibited non-normality as the residual analysis showed presence of both, skewness and kurtosis. Therefore, an additional impulse dummy was employed undertaking value 1 in 2008 Q4, in which the standard residual value of the variable STN_FI exceeded 3 standard deviation criteria. A new model, including impulse dummy variable, was still based on 1 endogenous lag, suggested by the Schwarz Criterion, excluding trend and intercept. Non-normality was efficiently removed and the diagnostic test did not show any signs of autocorrelation. Extreme but plausible forecasts, based on 99% bound on a confidence level are presented in the following table.

Table 20: Forecast for Belgium's worst-case macro scenario

Time	YER_BE	STN_BE	URX_BE
2011Q1	-0,1308	1,6919	8,6575
2011Q2	-1,9683	2,2308	9,0225
2011Q3	-3,6081	2,7043	9,3245
2011Q4	-5,0540	3,1187	9,5890
2012Q1	-6,3341	3,4845	9,8260
2012Q2	-7,4791	3,8117	10,0416
2012Q3	-8,5152	4,1081	10,2400
2012Q4	-9,4633	4,3800	10,4243

The bottom of the adverse scenario is hit at the end of 2012 with 9.5 % drop in GDP, 4.4 % interest rate and 10.5 % unemployment rate.

2.2.7.2 BELGIUM-SATELLITE MODEL

All the variables, including write-offs, which are denoted by WRO_NFC_BE, were again subjected to unit root tests. As stated before, the ADF test was used for this purpose and all the variables were found to be non-stationary. Again, all the variables were transformed to its first differences and proven to be stationary by the same procedure. In addition to that, all macro variables, except the write-offs, enter into the model as exogenous variables. In the Belgian case linking equation bases on 4 exogenous and 6 endogenous lags, excluding trend and intercept as statistically insignificant variables. The latter was suggested by 3 out of 4 info criteria. The model did not show any signs of autocorrelation, non-normality or instability. The restricted AR model with exogenous macro variables and endogenous write-offs variable is presented in the following table.

Table 21: The restricted satellite model for Belgium, with write-offs as endogenous variable and exogenous macro variables

Lags	WRO_NFC_BE_d1	STN_BE_d1	URX_BE_d1	YER_BE_d1
t	/		0,088**	0,093***
t-1		0,149***	0,177***	
t-2	0,507***	0,214***	0,185***	-0,200***
t-3		0,118***	0,203***	0,136***
t-4	-0,442***			-0,046***
t-5	-0,453***			

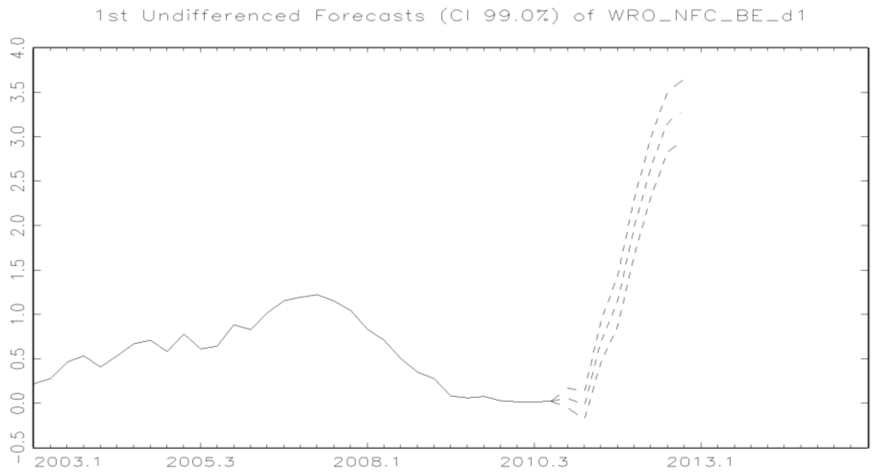
*Note: *** - significant at 1 %, ** - significant at 5 %*

As it can be seen from the upper table, all exogenous macro variables in summation behave according to the expectations, meaning that variables STN_BE and URX_BE exhibit a positive correlation with write-offs, whereas YER_BE exhibits a negative correlation. These correlations along with a macro forecast are then used to forecast future write-offs. An 8 quarter forecast is produced in order to capture at least 4 period forecasted macro shocks (2011 Q4) as the URX_BE shows a correlation with 4 lags. The results are presented in the table below.

Table 22: Write-offs forecast for Belgium with 99% upper and lower confidence levels

Time	Forecast	Lower CI	Upper CI
2011Q1	0,0567	-0,0549	0,1682
2011Q2	0,0000	-0,1831	0,1324
2011Q3	0,6976	0,4671	0,9281
2011Q4	1,1555	0,8703	1,4408
2012Q1	1,9917	1,6707	2,3128
2012Q2	2,6608	2,3255	2,9961
2012Q3	3,1708	2,8299	3,5116
2012Q4	3,3111	2,9701	3,6521

Figure 9: Write-offs forecast for Belgium with 99% upper and lower confidence levels



Focusing on the linking equation it could be inferred that the write-offs are mostly affected by the fluctuations in aggregate unemployment levels (URX_BE) and short-term interest rates (STN_BE). The impact of both variables appears to be quite strong in comparison to the other observed countries. A change in an unemployment level requires 3 quarters to fully reflect in an increased write-offs rate, while the strongest impact appears to be shown in the last quarter. The same amount of time is needed for the short-term interest rate to take effect, however, the effect is the strongest in the second quarter. All these findings could also be supported by observing the values of the forecasted write-offs and their graphical visualization. The macroeconomic shock comes into effect in the third quarter of 2011, which means two periods after its implementation. The write-off rate reaches the highest level of 3.3 % in the last forecasted period (2012 Q4). It could also be noticed that the write-offs even drop in the second quarter of 2011 as a result of a short rise in the Belgian employment level during the third and the fourth quarter of 2010.

2.2.8 GREECE

The macro model window ranges according to the shortest time series (YER_GR), from 2001 Q1 to 2010 Q4. In estimation of the linking equation the shortest time series is write-offs data for Greece (WRO_NFC_GR), meaning that the exogenous AR model is ranging from 2003 Q4 to 2010 Q4. Even though the number of observations is quite low, which makes it a hard case to examine, I decided to include Greece into our empirical research, since Greece has frequently been mentioned in recent periods. Short time-series data available for Greece with quickly exhausted degrees of freedom may in turn cause estimation problems and thus the unreliable results.

2.2.8.1 GREECE-MACRO SCENARIO ANALYSIS

The macro VAR model for the scenario analysis was initially based on 5 endogenous lags, suggested by the Final Prediction Error info criteria. The System Testing Procedure included trend and intercept as statistically significant variables in the model. All of the chosen variables were non-stationary and were transformed into first differences. The model exhibited non-normality as the residual analysis showed presence of both skewness and kurtosis. Therefore, an additional impulse dummy was employed, undertaking value 1 in 2008 Q4, in which the standard residual value of the variable STN_GR exceeded 3 standard deviation criteria. A new model, including the impulse dummy variable was still based on 5 endogenous lags, suggested by the Final Prediction Error, including trend and intercept. Non-normality was efficiently removed and the diagnostic test did not show any signs of autocorrelation. Extreme but plausible forecasts, based on 99% bound on a confidence level are presented in the following table.

Table 23: Forecast for Greece's worst-case macro scenario

Time	YER_GR	STN_GR	URX_GR
2011Q1	-11,6724	1,5034	15,2073
2011Q2	-15,8144	1,7709	16,0486
2011Q3	-18,9514	2,0332	16,5198
2011Q4	-21,4803	2,1724	16,6766
2012Q1	-23,0780	2,3997	16,9745
2012Q2	-23,8167	2,7391	17,1812
2012Q3	-24,3335	3,2185	17,6234
2012Q4	-24,3036	3,8899	18,1348

According to macroeconomic scenario, the Greek economic activity is expected to drop by more than 24 % at the end of 2012 and reach 18 % unemployment.

2.2.8.2 GREECE-SATELLITE MODEL

All the variables were found to be non-stationary. Again, all the variables were transformed to first differences. In the Greek case the linking equation is based on 4 exogenous, including trend and intercept as statistically significant variables. Even though 3 out of 4 info criteria suggested 1 endogenous lag to be used in the model, the lag order used was 2. The reason was an autocorrelation problem that was present in 1 lagged case (see sub-section 2.1.3). The model stopped showing signs of autocorrelation when 2 endogenous lags were adopted. There were no signs of non-normality or instability in the model. The restricted AR model with exogenous macro variables and an endogenous write-offs variable is presented in the following table.

Table 24: The restricted satellite model for Greece, with write-offs as endogenous variable and exogenous macro variables

Lags	WRO_NFC_GR_d1	STN_GR_d1	URX_GR_d1	YER_GR_d1
t	/			0,099***
t-1				-0,060***
t-2	-0,624***		0,359***	-0,055***
t-3		0,189***	-0,207**	-0,063***
t-4			0,248***	0,051***

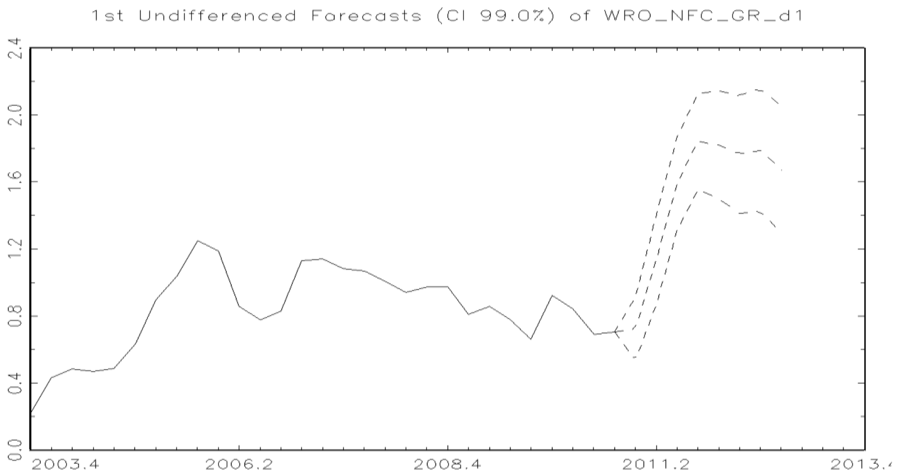
*Note: *** - significant at 1 %, ** - significant at 5 %*

As it can be seen from the upper table, all exogenous macro variables in summation behave according to the expectations, meaning that variables STN_GR and URX_GR exhibit a positive correlation with write-offs, whereas YER_GR exhibits a negative correlation. These correlations along with the macro forecast are used to forecast future write-offs. An 8 quarter forecast is produced in order to capture at least 4 period forecasted macro shocks (2011 Q4) as the URX_GR shows a correlation with 4 lags. The results are presented in the table below.

Table 25: Write-offs forecast for Greece with 99% upper and lower confidence levels

Time	Forecast	Lower CI	Upper CI
2011Q1	0,7238	0,5340	0,9136
2011Q2	1,1347	0,8662	1,4031
2011Q3	1,5904	1,3126	1,8682
2011Q4	1,8423	1,5555	2,1292
2012Q1	1,8211	1,4996	2,1427
2012Q2	1,7631	1,4103	2,1160
2012Q3	1,7924	1,4258	2,1589
2012Q4	1,6712	1,2915	2,0509

Figure 10: Write-offs forecast for Greece with 99% upper and lower confidence levels



Focusing on the linking equation it could be inferred that the write-offs are mostly affected by the fluctuations in aggregate unemployment levels (URX_GR) and short-term interest rates (STN_GR), while the all-in-all impact of GDP growth rate is small, but strongly significant. For example, a 3 lagged drop in GDP by 1 percentage point causes write offs rate to increase by approximately 0.06 percentage point. That is also the reason why write-offs do not respond to the macroeconomic shock as strongly as one would expect. The change in the unemployment level requires a whole year to fully reflect, while the strongest impact appears to be shown in the second quarter of a year. The amount of time that is needed for the short-interest rate to take effect appears to be a bit shorter (3 quarters). The overall macroeconomic shock comes into effect in the second quarter of 2011, which means two periods after its implementation. The write-off level reaches its peak at around 1.8 % in the last quarter of 2011 and remains fairly stable through the remaining of our forecasted periods.

2.2.9 MAIN REMARKS

The reputation of a country, based on the past economic performance, seems to play no significant role as far as the responsiveness of the write-offs data to the adverse macroeconomic scenario is concerned. For example, in cases of Germany and Belgium the highest responsiveness to macroeconomic shock was observed, whereas in cases of Italy or Greece the response was moderate. This would imply that Belgium banking system is among the least resilient to adverse macroeconomic development. However, it is worth noting that only the non-financial corporate portfolio was considered here. This may imply that the credit exposure might not be the main driver of the developing situation in currently troubled countries. It is also worth noting that probability of extreme scenarios constructed for each country in this analysis might differ among countries. In other words, it has to be considered how much of the particular scenario predicted in this analysis has been coming to life and in what countries. Also, in many cases the relationships between write-offs and macroeconomic variables were established during sound economic times which may differ in an adverse scenario. For example, in case of Germany in the pre-shock years, the write-offs rate was decreasing along with a good overall economic situation. These correlations were fully transferred to adverse scenario which might be a bit unrealistic to expect.

All in all, the projections are in line with the projections obtained in the 2011 EU-wide Stress Test conducted by the European Banking Authority, where default rates were predicted to reach a 2.5 % rate under the designed adverse scenario, showing a similar sensitivity to macro variables to the one observed by my analysis (EBA, 2011, p. 14).

2.3 CAPITALIZATION

Once the macro stress analysis for a particular country has been performed, the impact on banks' solvency and their balance sheet positions need to be examined. In the first part I briefly describe how these steps are usually undertaken in institutions such as ECB, while in the second part I describe the procedure which I have used in order to arrive to capitalization figures.

According to Schmeider, Puhr and Hasan (2011, p. 7) the objective of the solvency test is to determine whether capitalization levels of banks after stress are sufficient to (a) stay above regulatory minima, (b) meet market expectations (before the crisis the 4-8 % of capital was considered a good practice, whereas in the post crisis period this rate increased to 8-12 %), or (c) are sufficient to safeguard any particular bank of an additional idiosyncratic shock (uncorrelated shock). This allows determining potential capital needs in case either of these thresholds is not met. In my analysis I try to examine whether Tier 1 capital of a particular country's banking sector stays above threshold of a 5 % of risk weighted assets (RWA) after stress test was applied. This threshold value is used in accordance with the EU-wide Stress Test conducted by the European Banking Authority. The Tier 1 capital refers to the purest form of banks capital or core capital of a bank. It includes the banks' common stock and disclosed reserves (EBA, 2011, p. 2; Basel Committee on Banking Supervision, 2006, p. 244).

The Capitalization under stress is measured as follows (Schmeider, Puhr, & Hasan, 2011, p. 8):

$$Capitalization(t+1) = \frac{Capital(t) + Net\ income(t+1)}{RWAs(t+1)} \tag{17}$$

If a net income becomes negative under stress, this will hit the capital. In order to arrive to profit/loss figures which directly influence capital the procedure (18) is used (Schmeider, Puhr, & Hasan, 2011, p. 10):

Net Operating Income (18)

- Changes in Net Interest Income
- Changes in Net Fee and Commission Income
- Changes in Net Trading Income
- Loan Loss Provisions

= Pre Tax Profit

- Taxes
- Dividends

= Profit/loss (after stress, added to capital)

All the elements above can be subjected to a change when stress testing is applied. Namely, a stress test is performed by linking macro-economic forecasts to financial risk indicators. For example, loan loss provisions are calculated in the following way (Schmeider, Puhr, & Hasan, 2011):

$$\begin{aligned} &Loan\ Loss\ Provision \\ &\qquad = Loss\ Given\ Default\ (LGD) * Probability\ of\ Default (PD) \end{aligned} \tag{19}$$

If LGD or PD increases due to unfavourable macro-economic circumstances generated by a stress scenario, then loan loss provisions will increase which will adversely affect banks' profits and possibly erode capital. In such fashion all other changes are simulated into the income statement, which ultimately gives a direct statement on whether capital of a bank will increase or decrease. The most important parameters which have to be considered are: net operating income (which is a banks' first line of defence against unforeseen losses), RWA's (which influence the size of the necessary capital), PD's and LGD's (which influence the size of loan loss provisions).

Since the availability of data related to nonfinancial corporate (NFC) loans was very limited, I was forced to simplify the calculation of capital losses. The only relevant parameter which was available separately for NFC loans was write-off rates, which were forecasted in previous chapter for the period of 8 quarters (2011 and 2012). In the procedure of calculating capital losses I assumed that write-off rates (WRO_NFC) for a particular country, which are expressed as a percentage of total loans outstanding to NFC sector (LOAN_NFC_LEV), are directly transferred to capital losses:

$$Capital\ Loss = WRO\_NFC * LOAN\_NFC\_LEV \tag{20}$$

Since write-off rates were calculated for 8 quarters ahead, the last quarter in each year (2011 Q4 and 2012 Q4) was used in order to calculate capital losses for 2011 and 2012, respectively. The data for total loans outstanding to NFC sector was taken from 2010 Q4 and are assumed to be constant throughout the forecasting period. When capital losses for each year were calculated, I deducted these figures from Tier 1 core capital levels from 2010. Finally the remaining capital was used to calculate the new capitalization level for a particular national banking sector in 2011 and 2012 using RWA's levels from 2010. The exact calculation procedure is described below:

$$Capital\ Loss(2011) = WRO\_NFC(2011Q4) * LOAN\_NFC\_LEV(2010Q4) \quad (21)$$

$$Capital\ Loss(2012) = WRO\_NFC(2012Q4) * LOAN\_NFC\_LEV(2010Q4) \quad (22)$$

$$Capitalization(2011) = \frac{(Capital\ Core\ Tier\ 1(2010) - Capital\ Loss(2011))}{RWAs(2010)} \quad (23)$$

$$Capitalization(2012) = \frac{(Capital\ Core\ Tier\ 1(2010) - Capital\ Loss(2011+2012))}{RWAs(2010)} \quad (24)$$

Table 26: Capitalization

Column1	Spain	Germany	France	Portugal	Finland	Italy	Belgium	Greece
LOAN_NFC_LEV (2010Q4)	902135	817078	796562	120088	56471	865307	103541	98878
Capital core Tier 1 (2010)	136851	113306	161616	17933	5232	89831	28707	22778
RWA (2010)	1724305	1222402	1914086	233709	42724	1085459	252757	222466
Capital losses (2011)	8432,26	13231,76	1499,13	1550,46	729,10	4345,57	1196,42	1821,63
Capital losses (2012)	12027,26	25245,26	3886,43	2621,52	1232,76	8461,84	3428,35	1652,45
CAR (2010) (%)	7,94	9,27	8,44	7,67	12,25	8,28	11,36	10,24
CAR (2011) (%)	**7,45**	**8,19**	**8,37**	**7,01**	**10,54**	**7,88**	**10,88**	**9,42**
CAR (2012) (%)	**6,75**	**6,12**	**8,16**	**5,89**	**7,66**	**7,10**	**9,53**	**8,68**
EBA projections (%)	**6,5**	**6,8**	**7,5**	**5,2**	**11,6**	**6,5**	**10,2**	**5,7**

The shaded rows present capital adequacy ratios (CAR) for countries at the end of 2011 and 2012, reflecting capitalization positions after the stress scenario was introduced. It can easily be observed that all the countries have successfully withstood the stress-testing scenario, with Portugal as the only one falling below 6 %. The causality between the type of a country (troubled countries and non-troubled countries) and a write-off forecast was not significant, however, as far as the capitalisation (CAR) before the stress is concerned, the differences can be detected. Germany, France, Finland and Belgium all have CAR levels well above 8 % in 2010, whereas Spain and Portugal have slightly lower levels. For most of the countries considered in my sample, the obtained results are well aligned with projections calculated in the EU-wide Stress Test exercise. More significant deviations are only detected in the Greek and the Finish case. In the Greek case the obtained results clearly underestimate the impact of the potential macroeconomic crisis if EBA projections are considered as the benchmark. This can be ascribed to the fact that other types of portfolios and exposures may represent more important drivers of the current situation in the Greek banking system. In this particular case, the consideration of equity and sovereign exposure would most definitely provide additional information.

4 SLOVENIAN BANKING SYSTEM: EVIDENCE FROM PANEL VAR

After estimating the behaviour of bad loans with respect to macro variables in European countries for the purpose of examining the Slovenian banking system, I am interested in a more detailed micro level analysis with the implication to the whole system. The attempt is to examine the bank-specific indicators that might give an inside information signal to banking authorities about the overall banking system. Particularly, I will be interested in the determinants of the non-performing loans for the Slovenian banking system. In other words, how to give estimation about the health of the whole banking system from observing micro bank-specific variables? In order to bridge micro and macro framework, I am using Vector Autoregressive model with bank-specific panel data. The chapter is organised as follows: first I offer a brief overview of development and current general state of Slovenian banking system, in the second part I present the data and variables that enter my analysis, in third part the model for the analysis is presented, and at the end I offer estimation results along with the comments regarding the indicators of credit risk for the Slovenian banking system.

4.1 SLOVENIAN BANKING SYSTEM AND CREDIT RISK

Lending activity in Slovenia has been stagnating for the past three years. During this time the quality of banks' portfolios has deteriorated considerably. What is concerning is that companies that are receiving new orders are looking for funding in other foreign sectors (the interest rate in euro area is in average 2 percentage points lower than in Slovenia), meaning that Slovenian banks are losing profit opportunities and chances to restructure their portfolios. This means that the exposure towards companies with serious liquidity problems that are incapable of servicing their liabilities continues. Higher interest rates in Slovenia are in large part a consequence of reduced foreign financing and liquidity in crisis time, to which Slovenian banks responded by increasing interests on deposits. This means that operations of Slovenian banking system were not based on own funds and deposits in pre-crisis time, but were too heavily relied on foreign financing. Better portfolio quality has been detected among the banks with foreign ownership. The main restriction for the new lending remains high indebtedness of firms. The deterioration of banks' portfolios can be in a large part ascribed to the construction sector (Banka Slovenije, 2010, p. 26; Banka Slovenije, 2011, p. 31).

By the end of 2011 the level of nonperforming loans reached almost 6 billion EUR or 11.4 percent rate of the loan portfolio which represents a 4 percentage growth compared to the end of 2010. The quality of the portfolio is the worst in the non-financial corporate sector. Compared to 2010 the nonperforming loans rate grew by 10 percentage points, reaching almost 30 % of the whole loan portfolio for the eight largest Slovenian banks. As already mentioned, this large growth is mainly caused by the increasing number of bankruptcies in the construction sector. In the construction sector particularly the bad loans ratio reached 44 percent, rising from 20 percent in 2010. The structure and quality of the credit portfolio is the worst for the large and domestically owned banks, whereas for the banks with mainly foreign ownership this trend has successfully been averted. What is interesting is that the largest domestically owned banks record the smallest share of lending to a non-financial corporate sector in their portfolio, but exhibit twice as big rate of NPLs in that same sector compared to other banks. This reflects the bad management policies that have been present mainly in state owned banks in the recent years. The reason for this dynamics can be found in the large credit injections fuelled into domestically owned construction companies and also other companies associated with the government. On the other hand, the non-financial corporate sector represents the largest portion of the foreign banks' credit portfolio, but at the same time they record the smallest share of NPLs in that same sector compared to the other banks (Banka Slovenije, 2011, pp. 31-39).

The presence of the ongoing pessimism in the banking sector can be detected with respect to the banks' ratings of borrowers. Borrowers can be rated into five quality classes based on the ability to repay their liabilities, where A is being the least risky class and E the class encompassing borrowers that are not likely to meet their obligations. Similarly as it was the case with the NPLs, the credit rating structure of borrowers started to deteriorate in 2009 followed by the outburst of the economic crisis. In the first three quarters of the 2011 the rate of the best assessed borrowers (A and B ratings) dropped by more than 3 percentage points whereas the rate of the worst rated borrowers (D and E ratings) in the credit structure reached the point of 10 percent. In the whole four years period since the beginning of the crisis, the rate of borrowers rated with rates A or B decreased by 13.5 percentage points, while the rate of borrowers rated with D or E increased by 8.7 percentage points. One of the reasons for this might be the pro-cyclical behaviour of banks, which is a tendency of banks to grant better ratings in sound economic times, even though the financial performance of the borrowers does not differ considerably (see section 1.4.1). Banks also tend to give better ratings to the new borrowers, based on the fact that they have not yet experienced delayed payments with them. However, most of the credit rating structure can be ascribed to the developments in the non-financial corporate sector. More than 233 companies filed for bankruptcies in the second part of the 2010, whereas the number in the first part of 2011 reached 306 (Banka Slovenije, 2011, pp. 40-44).

4.2 DATA

In the analysis I am using bank-specific variables for the 8 largest banks (panel variable id) in Slovenia, where quarterly cross-sectional data are raging from 2006 Q1 to 2011 Q4 (time variable t). In addition to micro variables, the analysis also considers GDP variable which controls for the macroeconomic environment and serves as a comparison to bank-specific variables.

The particular variable of interest in the analysis of the Slovenian banking system is going to be NPL or ratio of non-performing loans. Non-performing loans are usually classified as Substandard, Doubtful or Loss and are by definition those loans that are overdue by more than 90 days. They are expected to behave in the same manner as the other measures of credit risk, meaning that the adverse economic scenario would push NPLs up. NPLs are more responsive than the write-offs used in the analysis in previous chapters (XU, 2005, p. 10).

Bank-specific determinants of NPLs have been described by Louzis, Vouldis, & Metaxas (2010, pp. 11-14), and Espinoza & Prasad (2010, p. 7). In these papers bank-specific factors are divided into categories which describe banks' policies with purpose to attain maximum efficiency and improvements in their risk management. These categories are management, a moral hazard, skimping, pro-cyclical credit policy and size:

- ***Management***: bank's management policies are described either by return on assets (ROA) or inefficiency. In a panel data frame return on assets can be written as:

$$ROA_{it} = \frac{Profits_{it} * 100}{Assets_{it}} \tag{25}$$

  Negative correlation with NPL is expected. Profit maximising policies should reflect themselves in stronger lending conditions in order to prevent NPLs from occurring. However, literature, for instance Boudriga, Taktak & Jellouli (2009, p.8), show an ambiguous correlation. They argue that especially in the developing countries profit maximising pressures tend to reflect in riskier lending activities. On the other hand, in developed countries banks prefer to use other non-credit revenues in response to profit maximising pressures. Another variable that could fall into this category is inefficiency, measured as operating expenses over operating income (expenses/income). Direction of the predicted impact is again ambiguous. One might connect low cost efficiency (bad management) with inability to assess creditworthiness, monitoring of borrowers financial statement and appraisal of collaterals. On the other hand, banks might be cost inefficient because they devote more resources in ensuring higher loan quality (skimping). In my analysis I am using the ROA as the measure of banks' management performance. Another measure used in the analysis is the bank-specific annualized weighted average interest rate AAR_{it}. Interest rates indicate banks margin, where I expect that higher margins will increase rate of problem loans.

- ***A moral hazard***: a moral hazard can be explained through the loan to deposit ratio, which can be formally written as:

$$LtD_{it} = \frac{Loans_{it}}{Deposit_{it}} \tag{26}$$

Loans to deposit ratio explains the moral hazard in a way that bank might seek to increase rate of loans not funded by deposits in order to boost current earnings at the expense of future problematic loans. Therefore LtD ratio is expected to have a positive correlation with NPLs. Another measure of the moral hazard could be solvency ratio, measured as capital over assets. Solvency ratio has a negative correlation with NPLs, since managers tend to increase riskiness of their loan portfolio when their banks are thinly capitalised. In my analysis I include LtD as a measure of a moral hazard.

- ***Pro-cyclical credit policy***: In the favourable macroeconomic condition banks tend to inflate their lending activity and by doing that extending their credit portfolio to worse borrowers in terms of the financial statement. In my analysis the bank's credit growth is denoted as:

$$gLOANS_{it} = \frac{loans_{it} - loans_{it-1}}{loans_{it}} * 100 \tag{27}$$

- ***Size***: The size of banks can be measured through the market power, which is bank's loans over the total banking system's loans, or through asset growth. Size is expected to be negatively correlated with NPL. However, variable size that would indicate growth in assets was excluded from the analysis, since it exhibits a high correlation with the growth of loans variable and thus does not offer any additional explanatory power.

4.3 MODEL

For the purpose of estimating responsiveness of the Slovenian banking system problem loans I used the panel data Vector Autoregressive model or the panel VAR, which in usual time series framework takes the following form[9]:

$$Y_{it} = a_0 + \sum_{l=1}^{m} Y_{it-l} + f_i + e_t, \tag{28}$$

where a_0 is a constant term, Y_{it} is a vector of bank-specific variables for the bank *i* at time *t*, and e_t is the disturbance factor (Holtz-Eakin, Newey, & Rosen, 1988, p. p. 1373). Since the model is based on the panel cross-bank data, it cannot be expected that this structure is completely the same for each cross-sectional unit, since some fixed bank-specific

[9] Note that this is a restricted form, compared to the one that was presented by Holtz-Eakin, Newey & Rosen (1988). They allow for cross-sectional unit heterogeneity by introducing individual specific intercept (allowing for cross-sectional changes in the mean) and individual specific innovation term. Their model takes the following form: $Y_{it} = a_{0t} + \sum_{l=1}^{m} Y_{it-l} + f_1 + e_{it}$

heterogeneity is likely to affect the process. In order to allow for this kind of an individual heterogeneity, fixed effects denoted as f_i are included in the model. One can imagine those unobserved effects as a propensity of an individual bank towards particular responsiveness of an endogenous variable in relation to other variables. Regressor term also contains lag dependant variables, which is why it is expected that individual unobserved effects are correlated with regressor term and subsequently also constant. The mean difference approach, which is commonly used to eliminate fixed effects, has proven to produce biased estimates when lagged dependant variables are included. Therefore, I used forward mean differencing approach or Helmert transformation of the parameters (Love & Lea, 2002, p. 10). Paper by Hayakawa (2009, p. 7) directly compares forward and first differencing, where he also proves better performance of the former method, for the purpose of GMM (Generalized Method of Moments) estimation. Variables of the model are therefore transformed in the following way:

$$y_{it}^* = y_{it} + w\left[\frac{y_{it+1} + \cdots + y_{it+m}}{t + m - 1}\right] \tag{29}$$

Once individual unobserved effects are removed, the model of interest undertakes the following reduced form:

$$Y_{it} = \sum_{l=1}^{m} Y_{it-l} + \sum_{l=1}^{m} GDP_{t-l} + e_t, \tag{30}$$

where $Y_{it} = (NPL_{it}, ROA_{it}, LtD_{it}, gLOANS_{it}, AAR_{it})'$ is the bank-specific variable vector. Note that the ordering of the variables in the vector is very important, since my analysis focuses on the impulse-response functions. Impulse-response functions and consequently the selection of ordering are described in sub-section 4.3.2. The GDP variable remains constant for each cross-sectional unit and only varies with time. The model parameters are identified with GMM estimator, described in the following sub-section.

4.3.1 GMM ESTIMATOR

The GMM estimator is becoming an ever more appealing method for identifying parameters for particular variables of interest due to its flexibility and consistency. It is especially useful in cases where distribution of data is unknown, it does not require imposition of restriction on the statistical behaviour of variables used and it is capable of overcoming the omitted variable bias problem, which is especially important for the models dealing with panel data. The omitted variable bias problem causes one or more explanatory variables to be correlated to the error term due to leaving out one or more important factors. This especially holds for the models with lagged dependent variable and panel data models where fixed cross sectional specific effects cannot be ignored. In these cases the OLS estimator is no longer unbiased and it tends to overestimate or underestimate one of the other factors included within the model (Alastair, 2010).

In order to estimate the unknown parameters for the explanatory variables, the GMM combines the information in population moment condition with economic data used in the model. Statistical moments can be described as the population average raised to the power number. For example, the r[th] statistical moment can be written as $\Upsilon_r = E[V_t^r]$ or expected value of V raised to the power of R. For example, the first statistical moment (r=1) is just the mean of population, second gives a variance of distribution, third tells the skewness, and fourth the kurtosis of distribution. These moments contain important information on aspects of given distribution. More general representation gives the population moment condition and can be written as the expected value of a function of observed economic data (V_t) and unknown parameter vector (Θ_0) being equal to zero for all t (Hansen, 2007, pp. 1-2):

$$E[f(V_t, \Theta_0)] = 0 \tag{31}$$

The above structure represents the population quantity, but for the purpose of operational GMM and estimation one would need a sample moment condition, which would replace the population average with a sample average:

$$T^{-1}\sum_{t=1}^{T} f(V_t, \Theta_0) = 0 \tag{32}$$

For the purpose of the example one can assume that economic data is normally distributed with unknown mean Θ_0 (what is to be estimated) and a known variance equal to one. The parameter vector Θ_0 can be then worked out from the population moment condition:

$$E[V_t] - \Theta_0 = 0 \tag{33}$$

By replacing population moment with the sample moment the equation can be turned into vehicle to produce estimates of the parameter vector:

$$T^{-1}\sum_{t=1}^{T} V_t - \widehat{\Theta_T} = 0 \tag{34}$$

Solving the equation gives the Method of Moments (MM) estimator:

$$\widehat{\Theta_T} = T^{-1}\sum_{t=1}^{T} V_t \tag{35}$$

Though the estimate might seem very intuitive it has some major weaknesses. Namely, the estimator was derived based on the extracted information from the first moment. However, the other moments also contain information about an unknown parameter vector, but as it turns out the estimates are not consistent when different moments are used. For instance, the second moment, given that it was assumed variance to be 1, would take the following form:

$$E[V_t^2] - \Theta_0^2 - 1 = 0 \tag{36}$$

Now the estimation is based not only on the information from the first moment but from the second moment as well. Meaning that in order to obtain the parameter estimates, two sets of equation with one unknown have to be solved where in general there is no exact solution for these two equations:

$$T^{-1}\sum_{t=1}^{T}V_t - \widehat{\Theta_T} = 0 \qquad\qquad T^{-1}\sum_{t=1}^{T}V_t^2 - \widehat{\Theta_T^2} - 1 = 0 \tag{37}$$

To allow for estimates based on more than one population condition the generalization of MM needs to be done, thus the GMM estimator. The GMM estimator of Θ_0 is exploiting information in general form of population moment condition ($E[f(V_t, \Theta_0)] = 0$) and is defined to be the value of Θ that minimizes the function $Q_T(\Theta)$, where the $Q_T(\Theta)$ is just a quadratic form of the sample moment condition with weighting matrix W_T:

$$\widehat{\Theta_T} = argmin_{\Theta\in\Theta} Q_T(\Theta) \tag{38}$$

$$Q_T(\Theta) = T^{-1}\sum_{t=1}^{T} f(V_t, \Theta_0)' \, W_T T^{-1}\sum_{t=1}^{T} f(V_t, \Theta_0) \tag{39}$$

In other words, the GMM estimates the value that minimizes the distance from $Q_T(\Theta)$ to zero. The $Q_T(\Theta)$ can be therefore also referred to as the measure of closeness to zero, whereas the weighting matrix simply assigns the weight to the particular coordinate in the distance. As an example again consider the case where information out of first two moments is to be extracted. Then the two-dimensional vector can be defined with first moment information on top and second moment bellow (Alastair, 2010):

$$f(V_t, \Theta_0) = \begin{bmatrix} E[V_t] - \Theta_0 \\ E[V_t^2] - \Theta_0^2 - 1 \end{bmatrix} = \begin{bmatrix} g_a \\ g_b \end{bmatrix} \tag{40}$$

If the weighting matrix is a simple identity matrix $W_T = I_2$, then the coordinates are equally important. Alternatively the weighting matrix used in the example bellow attaches the greater importance to the first coordinate in the distance:

$$Q_T(\Theta) = f(V_t, \Theta_0)' W_T f(V_t, \Theta_0) = \begin{bmatrix} g_a & g_b \end{bmatrix} \begin{bmatrix} 2 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} g_a \\ g_b \end{bmatrix} = 2{g_a}^2 + {g_b}^2 \tag{41}$$

It turns out that the optimal choice of the weighting matrix is the one that minimizes the population variance of the sample moment (S), meaning that $W=S^{-1}$. But this imposes difficulties in implementing the GMM, since for the calculation of S the estimates of the parameter vector Θ_0 are needed. The GMM is therefore implemented in a two-step or in a multi-step iterative process, where in the first step the identity matrix is used W=I in order to produce preliminary parameter estimates which are then used in the ensuing steps (Alastair, 2010).

From the above description some concluding characteristics concerning the GMM method can be pulled. Let the dimensions of $f(.)$ be q×1 and dimensions of Θ be p×1. If q=p then simple MM applies and the structure is independent from W. If q is greater than p, then the GMM estimator is the value of Θ closest to solving sample moment condition and $W= S^{-1}$.

4.3.2 IMPULSE RESPONSE FUNCTIONS

The above PVAR structure represents the so called standard form of the VAR or unstructured VAR. It is the normalization of the structural VAR (SVAR), in the sense that it eliminates contemporaneous effects. It means that it is under-identified and that some restrictions need to be imposed in order to identify coefficients and the impulses. To explain this I present the example described in Enders (1995, pp. 294-297;305-307), which considers the following two variable models of the first order:

$$y_t = b_{10} - b_{12}z_t + c_{11}y_{t-1} + c_{12}z_{t-1} + \varepsilon_{yt} \tag{42}$$

$$z_t = b_{20} - b_{21}y_t + c_{21}y_{t-1} + c_{22}z_{t-1} + \varepsilon_{zt} \tag{43}$$

where ε_{it} is white noise, i.i.d (0, $\sigma_{\varepsilon i}^2$) and cov($\varepsilon_y, \varepsilon_z$). This is the Structural VAR and can be rewritten in a matrix form:

$$\begin{bmatrix} 1 & b_{12} \\ b_{21} & 1 \end{bmatrix}\begin{bmatrix} y_t \\ z_t \end{bmatrix} = \begin{bmatrix} b_{10} \\ b_{20} \end{bmatrix} + \begin{bmatrix} c_{11} & c_{12} \\ c_{21} & c_{22} \end{bmatrix}\begin{bmatrix} y_{t-1} \\ z_{t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{yt} \\ \varepsilon_{zt} \end{bmatrix} \tag{44}$$

or more simply:

$$BX_t = \Gamma_0 + \Gamma_1 X_{t-1} + \varepsilon_t \tag{45}$$

The left hand side can be normalized by multiplying the equation by B^{-1}, which gets us to:

$$B^{-1} = \frac{1}{(1 - b_{21}b_{12})}\begin{bmatrix} 1 & -b_{12} \\ -b_{21} & 1 \end{bmatrix} \tag{46}$$

$$\begin{bmatrix} y_t \\ z_t \end{bmatrix} = \begin{bmatrix} a_{10} \\ a_{20} \end{bmatrix} + \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}\begin{bmatrix} y_{t-1} \\ z_{t-1} \end{bmatrix} + \begin{bmatrix} e_{1t} \\ e_{2t} \end{bmatrix} \tag{47}$$

or more simply

$$X_t = \mathrm{A}_0 + \mathrm{A}_1 X_{t-1} + e_t, \tag{48}$$

where the error terms are composites of the structural innovations (from SVAR). The variances of error terms are serially uncorrelated or time invariant, but they are correlated across equations, meaning that covariances are not 0:

$$\begin{bmatrix} e_{1t} \\ e_{2t} \end{bmatrix} = \frac{1}{(1 - b_{21}b_{12})}\begin{bmatrix} 1 & -b_{12} \\ -b_{21} & 1 \end{bmatrix}\begin{bmatrix} \varepsilon_{yt} \\ \varepsilon_{zt} \end{bmatrix} \tag{49}$$

The purpose of the estimation is to observe how structural innovation ε_{it} affects the dependent variables. From the equation above it is clear that for this parameters from SVAR need to be recovered. However, since in my analysis I am estimating VAR in standard form, the SVAR is under-identified. Namely, VAR consists of 9 parameters (6 coefficient estimates, 2 variances, 1 covariance), while SVAR consists of 10 parameters (8 parameters, 2 variances). Therefore, some restrictions have to be imposed. With triangular decomposition of (variance covariance matrix) or Cholesky decomposition one can assume that b_{21}=0, or in other words, y is affected by structural innovations of y and z, while z is only affected by its own structural innovations:

$$B^{-1} = \frac{1}{(1-b_{21}b_{12})}\begin{bmatrix} 1 & -b_{12} \\ -b_{21} & 1 \end{bmatrix} = \begin{bmatrix} 1 & -b_{12} \\ 0 & 1 \end{bmatrix} \tag{50}$$

By imposing this constraint, the SVAR can be exactly identified, since there are 9 parameter estimates and 9 unknown structural parameters (Enders, 1995, p. 303).

The SVAR becomes:

$$\begin{bmatrix} 1 & b_{12} \\ 0 & 1 \end{bmatrix}\begin{bmatrix} y_t \\ z_t \end{bmatrix} = \begin{bmatrix} b_{10} \\ b_{20} \end{bmatrix} + \begin{bmatrix} c_{11} & c_{12} \\ c_{21} & c_{22} \end{bmatrix}\begin{bmatrix} y_{t-1} \\ z_{t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{yt} \\ \varepsilon_{zt} \end{bmatrix} \tag{51}$$

From that, the VAR system can be derived as:

$$\begin{bmatrix} y_t \\ z_t \end{bmatrix} = \begin{bmatrix} b_{10} - b_{12}b_{20} \\ b_{20} \end{bmatrix} + \begin{bmatrix} (c_{11} - b_{12}c_{21}) & (c_{12} - b_{12}c_{22}) \\ c_{21} & c_{22} \end{bmatrix}\begin{bmatrix} y_{t-1} \\ z_{t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{yt} - b_{12}\varepsilon_{zt} \\ \varepsilon_{zt} \end{bmatrix} \tag{52}$$

By matching this derived VAR structure with the original standard form VAR, one can extract the coefficients of the SVAR.

This can be similarly applied to impulse response functions (IRF). IRF is in essence the moving average representation of the VAR. Therefore, one first has to transform the VAR into vector moving average (VMA) representation to analyze the dynamic relations among the variables in the VAR (Lopes & Migon, 1994, pp. 2-3):

$$\begin{bmatrix} y_t \\ z_t \end{bmatrix} = \begin{bmatrix} \bar{y} \\ \bar{z} \end{bmatrix} + \sum_{i=0}^{\infty} \underbrace{\begin{bmatrix} \mathrm{a}_{11} & \mathrm{a}_{12} \\ \mathrm{a}_{21} & \mathrm{a}_{22} \end{bmatrix}^{i}}_{\mathrm{A^i}} \begin{bmatrix} e_{1,t-i} \\ e_{2,t-i} \end{bmatrix} \tag{53}$$

In order to examine dynamic relations, composite errors $e_t$have to be replaced with structural innovations ε_t:

$$e_t = \frac{1}{|.|}\begin{bmatrix} 1 & -b_{12} \\ -b_{21} & 1 \end{bmatrix}\varepsilon_t \tag{54}$$

Considering that, the structure can be rewritten as:

$$\begin{aligned} \begin{bmatrix} y_t \\ z_t \end{bmatrix} &= \begin{bmatrix} \bar{y} \\ \bar{z} \end{bmatrix} + \sum_{i=0}^{\infty} \underbrace{\frac{A^i}{1-b_{12}b_{21}}\begin{bmatrix} 1 & -b_{12} \\ -b_{21} & 1 \end{bmatrix}}_{\Phi_i}\begin{bmatrix} \varepsilon_{y,t-i} \\ \varepsilon_{z,t-i} \end{bmatrix} = \\ &= \begin{bmatrix} \bar{y} \\ \bar{z} \end{bmatrix} + \sum_{i=0}^{\infty} \begin{bmatrix} \Phi_{11}^{(i)} & \Phi_{12}^{(i)} \\ \Phi_{21}^{(i)} & \Phi_{22}^{(i)} \end{bmatrix}^{i} \begin{bmatrix} \varepsilon_{y,t-i} \\ \varepsilon_{z,t-i} \end{bmatrix} = \bar{X} + \sum_{i=0}^{\infty} \Phi_i\, \varepsilon_{t-i} \end{aligned} \tag{55}$$

Impact multipliers examine the effect of a one unit change in a structural innovation i.e.:

$$\frac{dy_t}{d\varepsilon_{z,t}} = \Phi_{12}(0); \frac{dz_t}{d\varepsilon_{z,t}} = \Phi_{22}(0); \frac{dy_{t+1}}{d\varepsilon_{z,t}} = \Phi_{12}(1); \frac{dz_{t+1}}{d\varepsilon_{z,t}} = \Phi_{22}(1) \tag{56}$$

As already described, in practice these effects cannot be calculated since SVAR is under-identified. So again, restriction on VAR has to be assumed. As an example, let reversed situation to the above described before be assumed, meaning that the upper triangular Cholesky decomposition of the variance-covariance matrix is assumed, $b_{12} = 0$:

$$\begin{bmatrix} e_{1t} \\ e_{2t} \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ -b_{21} & 1 \end{bmatrix} \begin{bmatrix} \varepsilon_{yt} \\ \varepsilon_{zt} \end{bmatrix} \tag{57}$$

According to this decomposition, the shock ε_{zt} does not affect y directly but only indirectly through lagged effect of z, while ε_{yt} affects z contemporaneously and with lag. Therefore, variables that come earlier in the system, affect the following variables contemporaneously and with lag, while the later variables affect previous only with lag (Love & Lea, 2002, p. 8).

Based on that I formulated the ordering of variables already mentioned before: $Y_{it} = (NPL_{it}, ROA_{it}, LtD_{it}, gLOANS_{it}, AAR_{it})'$. It was assumed that NPL affects all the variables contemporaneously and with lag, while the NPL rate is affected by the other variables just with lag. The reasoning for that is in the transmission of shock. The interest rate is a direct policy instrument of banks and is thus expected to be the most endogenous variable in the set. The endogenous policy change in form of reduced interest rate will cause lagged response in credit growth, which will consequently affect loan to deposit ratios and latest returns on assets. All variables, however, have a lagged effect on the rate of NPLs. The shock in NPL, on the other hand, will be instantly materialized in returns (ROA), which will force banks to react with the interest rate (AAR) and consequently affect the portfolio position (LtD and gLOANS).

4.4 ESTIMATION RESULTS

The 3 lag panel VAR with explained vector Y_{it} and GDP variable was estimated. As already mentioned, the panel VAR is estimated with the GMM method. It formulates 6 equations (for each endogenous variable included). In the following table I only present the estimated coefficient for the equation, where NPL is the dependent variable:

Table 27: Estimated PVAR (equation for NPL as dependent variable)

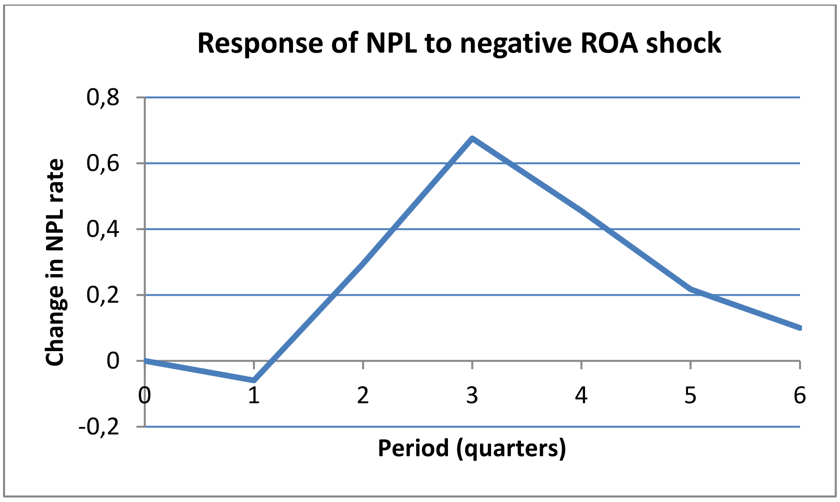
Lags	NPL	ROA	LtD	gLOANS	AAR	GDP
t-1	1,126***	0,114	1,054	-0,085*	-0,119	-0,016
t-2	-0,113	-0,692**	-1,159	-0,062	0,071	0,001
t-3	-0,034	-1,087***	4,217**	-0,057	0,053	-0,311**

*** - significant at 1 %, ** - significant at 5 %, * -significant at 10 %

From the results it may be observed that lagged dependent variable has a positive sign in the first period, whereas in the following two periods it exhibits a negative correlation. The explanation for the change in signs is that NPL ratio tends to decrease if it has increased in the past periods due to their transformation into the write-offs. Same findings can be observed in the analysis done by Louzis, Vouldis, & Metaxas (2010, p. 22) for the Greek banking system, or in the case of the Finish banking system examined by Sorge and Virolainen (in Louzis, Vouldis, & Metaxas, 2010, p. 22). However, in the case of Slovenian banking system the dependence seems to be the strongest and statistically significant only in the first lag, where the correlation is positive.

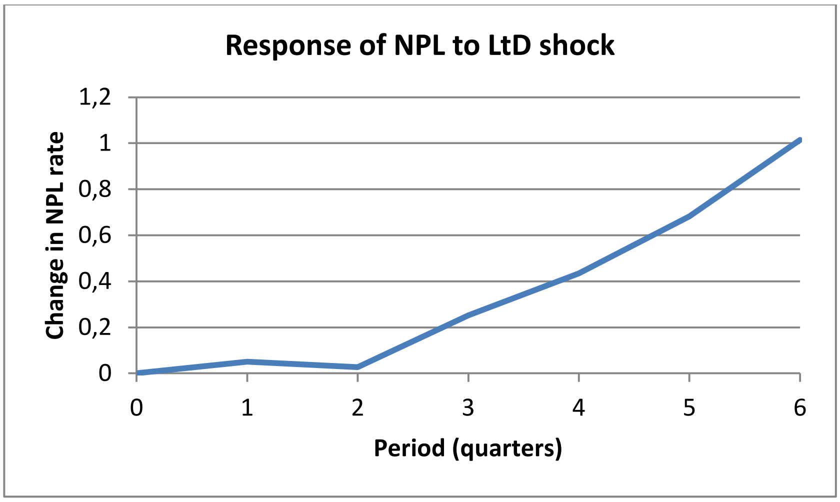
The estimated coefficients for the ROA variable confirm the bad management hypothesis, proving that lagged performance is negatively correlated with the problem loans. In other words, reduced past earnings seem to be a strong indicator of the quality of banks' management as far as the granting loans and estimating the borrowers is concerned. The coefficient is statistically most significant in the third lag where decrease of returns by 1 percentage point induces increase in NPL ratio by 1.087 percentage point. The impulse response to a one standard deviation negative shock in ROA is depicted in the Figure 11. After a slight initial reaction, the response quickly rises and reaches the peak after three quarters, as expected. The effect wears off relatively slowly after 7 quarters.

Figure 11: Impulse response of NPL to ROA shock



Banks' risk attitude (LtD) reflects expected and strong explanatory power in the third period lag, where 1 percentage point increase in loans not covered by deposits is reflected in 4.217 percentage point increase in bad loans. This result implies the ongoing presence of moral hazard incentives in the Slovenian banking system, which cause bank managers to involve in reckless risk-taking that generates high levels of NPLs. This means that overview of the riskiness of individual bank's loan portfolio in Slovenian banking system is still not done accurately enough and that stricter interventions by authorities may be needed. From Figure 12 it can be observed that response of NPL rate to one standard deviation shock in LtD ratio is relatively slow, but increasing rapidly after the first significant reaction in the third quarter.

Figure 12: Impulse response of NPL to LtD shock



As far as the credit growth is concerned the model was not able to explain the movement of the NPL ratio with the past credit growth. Furthermore, the results are demonstrating a negative correlation, rejecting the procyclical credit growth hypothesis set initially. Comparing this result with estimated coefficients on LtD it may be assumed that extensive lending policy does not necessarily reflect reckless risk-taking and hazardous behaviour. Therefore, the LtD ratio may be considered as the stronger short-term explanatory indicator of the loan performance. Another explanation for negatively signed credit growth coefficients is that procyclical credit policy cannot be considered as a short-term indicator of the NPLs, since it may take up to three or four years for increased loans to transform into bad loans. This is due to the fact that the credit growth coincides with the upward business cycle, meaning that loans are granted in the sound times when firms have steady and sufficient streams of income. Contrary, in the adverse economic times when general confidence of economic agents is low banks tend to be more conservative on expanding their portfolios whereas the existing loans are generating evermore NPLs. This strong negative short-term to medium-term correlation can also be observed in the latest crisis where the credit growth has been stagnating or even decreasing for the last three years, while the NPL rate has been increasing at a staggering pace. In other words, it would be naive to expect no endogenous response from banks. It is not reasonable to think that bank managers would be willing to increase the portfolio that has been hit by the crisis. It is then important to observe also the potential feedback effect of deteriorating loan performance on credit growth. Indeed the variance decomposition shows that much greater percentage variation in credit growth can be explained by a variation in NPL rate (36 %) than vice versa (20 %). The feedback impulse response indicates significant contemporaneous feedback response of credit growth to the shock in the NPL rate. After immediate drop by more than 1 percentage point, the feedback effect also seems to be very persistent.

Figure 13: Impulse response of NPL to growth of loans shock

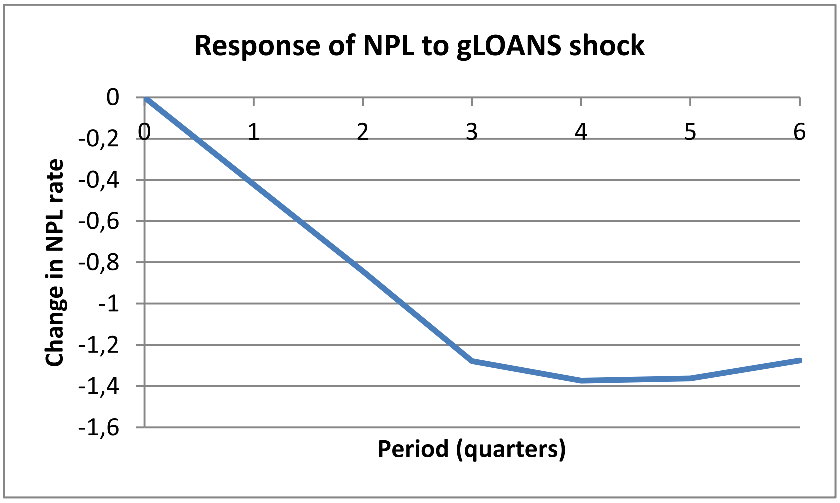
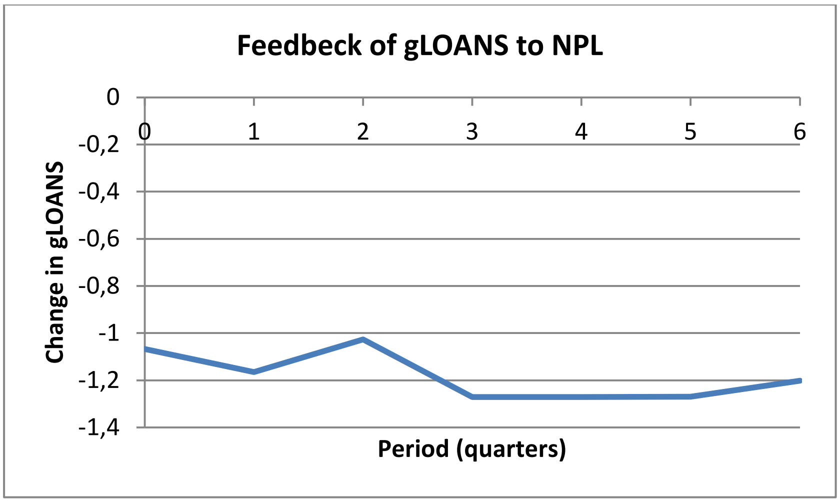
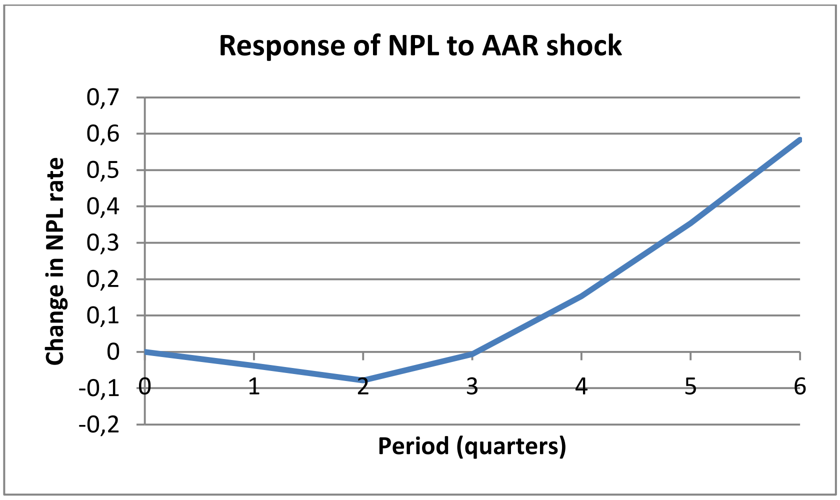


Figure 14: Feedback effect on growth of loan



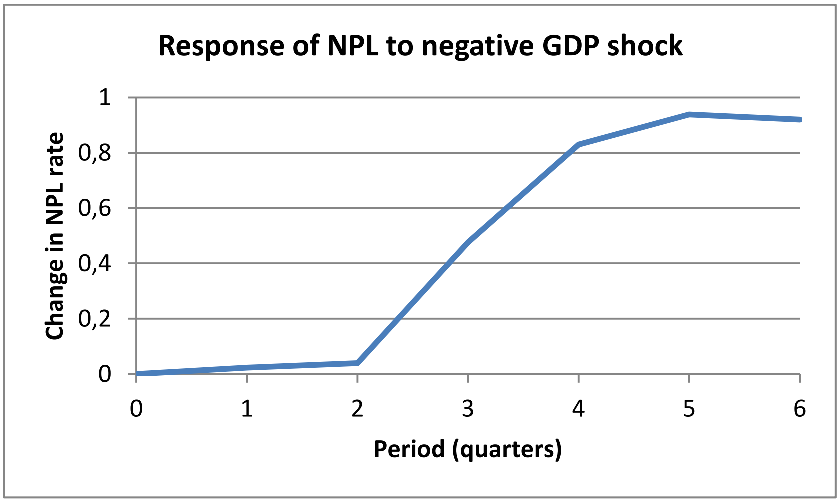
However, the credit growth has also been decreasing due to the lower credit demand. Downward economic activity reduces the level of firms' contracts and new projects for which they would need new streams of funding. To boost economic activity authorities usually reduce the reference interest rate which with constant interest margins reduces interest rates on new as well as on the existing loans. From the data on Slovenian banking system the rising number of NPLs coinciding with lower or constant banks' interest rates could therefore be observed. In the short-term period this contradicts the initial hypothesis saying that lower interest rate should reduce the bad loans rate. It is not surprising then that coefficients estimated for the AAR are insignificant along with the negative correlation exhibited in the impulse response in the first three quarters. The long-term response on the other hand is expected and aligned with the initial hypothesis.

Figure 15: Impulse response of NPL to interest rate (AAR) shock



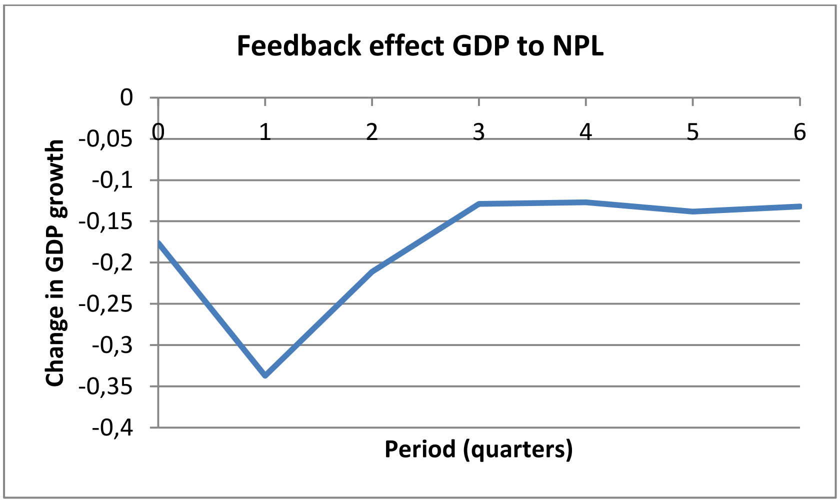
Although micro variables have been examined the bank-specific NPLs seems to be still equally well explained by the general macro environment. The variable indicating the GDP growth acts according to the theory and the initial expectation. Except for the second lagged quarter where a small and statistically insignificant positive relationship is detected, the rise of GDP negatively affects the growth of NPL. For instance, the rise of GDP by 1 percentage point would reduce NPL rate by 0.311 percentage point three periods ahead. The impulse response to a negative one standard deviation shock is depicted in figure 16.

Figure 16: Impulse response of NPL to GDP shock



However, the increasing rate of NPLs also has a potential feedback effect on the macro-economy. In the figure 17 a possible credit crunch was demonstrated, which is in turn reflected also in reduced GDP rate. The variance decomposition shows that almost 9 percent variation in GDP can be explained by the variation in NPL rate. The impulse response function indicates a 0.337 percentage point decrease in the GDP growth in the first quarter after a one standard deviation shock in NPL rate.

Figure 17: Feedback effects on GDP



CONCLUSION

Stress-testing reached its dimensions with Basel Capital Accord when it was formally introduced into the financial stability analysis. Ever since, techniques have evolved considerably and stress-testing has become a regular practice of all larger financial institutions, as well as of the supervisory and non-supervisory authorities. Stress-testing exercise is a multi-step process starting with construction of scenario that translates a stress event into a macroeconomic environment. Scenario can be designed by considering historically worst observations (a worst-case scenario) at a given plausibility or by considering the so called threshold approach. In the latter case a practitioner would be interested in the size of a shock that would completely exhaust banking system capacities. In that case, hypothetical scenarios could be brought into consideration. In general, macro-econometric models do not directly link macroeconomic variables to banks' portfolio data. Exceptions are the unstructured models (i.e. VAR including impulse responses), in other cases a satellite model that links macro variables to banks' data has to be introduced. A satellite model can be based on the loan performance data or on the individual borrower data. It has been proven that models based on the individual borrower data detect difficulties much earlier and are far more accurate than models based on loan performance. The individual borrower approach is also used in analysing credit risk by the Bank of Slovenia, where migrations of borrowers among 5 rating classes are examined. The credit analysis in Slovenia is done in a bottom-up manner, meaning that the aggregate financial system is examined. Contrary, the EU-wide stress tests are done in a top-down approach, meaning that main assumptions on macroeconomic conditions are provided by the authority, whereas their application is left to individual banks' internal models. The top-down approach usually offers more comparable results, but is less accurate than bottom-up approach, and, in addition to that, it fails to capture individual banks' complexities and contagion channels. The model choice is highly dependent on the established objectives, which could be validation (capital calculation), decision making and communication (storytelling). For the purpose of communication, the structural econometric models tend to be more favourable since they are backed with economic theory, whereas the VAR models offer greater flexibility and accuracy needed when the validation is the main objective.

For the purpose of stress-testing exercise, the macroeconomic scenario was designed based on the adverse projected movements in 3 macroeconomic variables: GDP growth, short-term interest rate and unemployment rate. The projected values of macroeconomic variables were linked to the write-offs data for each individual country. The established correlations between the write-offs data and the macroeconomic variables were in accordance with the initial assumptions. Based on the projected values of write-offs, currently troubled countries (Italy, Spain, Greece and Portugal) could not be proven to be any more susceptible to adverse macroeconomic movement than the other benchmark European countries are (Germany, Belgium, Finland and France). In average, the projected value of write-offs rate seems to be well aligned with the default projections obtained in the 2011 EU-wide stress test (2.5 %). Also projections on Tier 1 capital for each country seem to be complied with the EBA projections on Tier 1 for the same countries. The only larger deviation could be detected in case of Greece, where the model used in the thesis clearly underestimates (if EBA is considered to be the benchmark) the effects on the Greek banking system.

In the last part the Slovenian banking system was examined. The emphasis was on establishing the bank-specific determinants of the non-performing loans and offering a new concept that would bridge micro and macro stress analysis. In addition to establishing interdependencies among variables, the response of NPLs to shock in bank-specific variables was examined. The bank-specific variables used in the analysis were the return on assets (ROA), the loan to deposit ratio (LtD), the credit growth and the weighted average interest rate. The ROA variable, which is the indicator of banks' management performance, exhibits a strong correlation with Slovenian NPLs. This could be interpreted as the inability of managers in terms of granting new loans and properly rating the borrowers. However, the strongest indicator seems to be the loan to deposit ratio. This result implies the ongoing presence of moral hazard incentives in the Slovenian banking system, which cause bank managers to involve in reckless risk-taking that generates high levels of NPLs. No significant correlation for procyclical credit policy or interest rate could be established. Compared to results on LtD, this might infer that extensive lending policy does not necessarily reflect reckless and hazardous behaviour. Further, credit growth appears to be a long-term indicator of the troubled loans since it may take up to 3 years to fully materialize in NPLs. In addition to that, during the crisis the rising NPLs rate with stagnating credit growth could have been observed, which significantly affects the short-term relationship to be the opposite of the expected. And indeed, the GDP, as a variable controlling for the macroeconomic activity, appears to offer much more information than credit growth as far as the explanation of NLPs is concerned. NPLs also seem to have large feedback effect on both the NPLs and the GDP growth. In fact, according to the variance decomposition, a much greater variation of credit growth can be explained by NPLs than vice versa.

POVZETEK

V preteklih letih smo bili lahko priča uničujoči sili finančnih kriz, katere vse do danes ne pojenjajo. Tako ni presenetljivo, da je področje finančne stabilnosti postalo eno izmed poglavitnih vprašanj ekonomske in politične stroke. Finančna stabilnost je lahko opredeljena kot zmožnost finančnega sistema, da prenese zunanje šoke in nadaljuje z opravljanjem svojih ključnih dejavnosti. Tako finančna stabilnost ne implicira brezhibnega finančnega sistema, temveč se nanaša na sistem, ki je sposoben prepoznati nevarnosti in preprečiti, da bi le te postale sistemske. V tem pogledu je razvoj analitičnega okvirja, ki bi *ex ante* določil verjetnost in jakost potencialnih sistemskih kriz, postal ultimativni cilj finančnih nadzornih institucij ter ostalih organov, ki jih omenjeno področje dosega. Ocenjevanje finančne stabilnosti se nanaša na analizo kvalitativnih informacij, ki se nanašajo na institucionalne in regulatorne smernice, kot tudi na kvantitativno analizo, v katero spadajo tudi stres testi.

Tako je stres teste mogoče opredeliti kot nabor statističnih metod, namenjenih ocenjevanju ranljivosti finančnega sistema v primeru ekstremnega, a še vedno verjetnega šoka. Sodeč po tem je stres teste moč dojeti tudi kot prognostično orodje in v tem kontekstu lahko služijo kot zgodnji opozorilni sistem.

Prve stresne analize so se pojavile v zgodnjih 90-tih letih prejšnjega stoletja in so bile večinoma uporabljene v domeni velikih finančnih institucij in bank. Prevladujoča metoda tistega časa je bila metoda mere tveganja (Value at Risk – VaR), ki je bila široko sprejeta kot rešitev za vprašanje upravljanja s tveganji. Vendar pa je omenjena metoda le kratek čas kazala dobre rezultate, saj so prve večje krize, ki so sledile, kmalu razkrile vse njene slabosti. Ena večjih pomanjkljivosti VaR metode je ta, da je povsem nedovzetna za dogajanje v repih distribucije. Pove nam namreč največjo možno izgubo posamezne naložbe v danem časovnem intervalu oziroma pri dani verjetnosti. Na primer, pove nam največjo možno izgubo v 95 izmed 100 dni, vendar pa kot se je izkazalo, je ravno dogajanje v preostalih 5 dneh ključno za delovanje finančnih institucij.

Tako so se kot posledica omenjenih slabosti VaR metode pojavili stres testi, ki ocenjujejo učinke poljubno ekstremnih finančnih dogodkov. Da bi bila zagotovljena objektivnost stres testov, so scenariji običajno omejeni s predpostavko ″ekstremni, a še verjetni″. Stres testi torej morajo temeljiti na določeni verjetnosti, da bi ohranili celotno analizo smiselno. S tako imenovano Basel regulacijo o minimalnih kapitalskih zahtevah (1996) so stres testi dobili formalno podlago in so postali zahtevan in sestavni del kalkulacije kapitalske ustreznosti. Basel II regulacija (2004) je področje delovanja stresne analize samo še poglobila in jo razširila na vse vrste tveganja. Poleg uporabe stres testov za potrebe izračunavanja kapitalske ustreznosti posameznih bank so tudi makroekonomski stres testi v drugi polovici prejšnjega desetletja postali vsesplošna praksa bančnih in finančnih nadzornih institucij. Prav tako so obsežne analize tveganja finančnega sektorja redna aktivnost tudi ostalih institucij, kot so na primer Mednarodni Denarni Sklad.

Sodeč po zgoraj opisanemu se dejavnost in sama oblika stres testov lahko razlikuje glede na cilje in namene stresne analize. Tako je moč razlikovati stres teste za notranjo ali zunanjo uporabo. Glavni cilj stres testov namenjenih za notranje potrebe so validacija (kalkulacija kapitalske ustreznosti) in sprejemanje odločitev. Tovrstni stres testi bodo stremeli k natančnosti in ne v tolikšni meri k pojasnjevalni funkciji. Prav nasprotno bodo stres testi, katerih glavni cilj je komunikacija, želeli čim večjo pojasnjevalno moč modela v smislu prepoznavanja tveganj in kanalov prenosa šoka, medtem ko natančnost ne bo prioriteta. Obravnavano delo temelji na stres testih, ki analizirajo celoten sistem, in ne na individualnih stres testih.

OPREDELITEV CILJEV IN STRUKTURE

Prvi del magistrske naloge je namenjen postavljanju teoretičnega in analitičnega okvirja. Namen poglavja je opredeliti posamezne dele stresne analize in določiti ter prepoznati korake, ki so nujni za uspešno izvedbo procesa. V nadaljevanju analiziram različne metodologije, ki so bile do sedaj uporabljene s strani različnih institucij po celem svetu. Namen tega je opredeliti dobrobiti in slabosti posameznega izbranega pristopa k stresni analizi in na ta način omogočiti njihovo primerjavo. V sklepnem delu poglavja je posebna pozornost namenjena metodologiji in izkušnji iz Slovenije ter Evropske Unije (pri EU je poudarek na Evropski Centralni Banki in Evropski Bančni Agenciji, ki predstavljata nadnacionalne bančne nadzorne organe).

V drugem delu ponujam lasten prispevek k stresni analizi in aplikacijo stresnega procesa (opisanega v prvem delu) na reprezentativne bančne sisteme držav evro območja. Cilj bo analizirati odzivnost in odpornost bančnih sistemov na makroekonomske šoke ter preveriti njihovo kapitalsko ustreznost. Pri tem je poseben poudarek namenjen določanju korelacij med makroekonomskimi spremenljivkami in spremenljivkami, ki določajo kvaliteto portfelja. Vzorec ne eni strani vključuje 4 države, za katere velja, da se težje soočajo s trenutno krizo, in na drugi strani 4 države, ki naj bi bile postavljene kot merilo uspešnosti. Tako je namen tudi preveriti hipotezo, ki pravi, da so bančni sistemi uspešnejših držav manj dovzetni za makroekonomsko dogajanje.

Zadnji del se nanaša na stresno analizo slovenskega bančnega sistema. Tu bo cilj demonstrirati agregatne učinke na bančni sistem preko uporabe bankam-specifičnih spremenljivk. Cilj poglavja je namenjen določanju determinant slabih kreditov v slovenskem bančnem sistemu. Namen je torej določiti bankam-specifične spremenljivke, ki bi služile kot zgodnji opozorilni sistem glede finančne stabilnosti. Prav tako je namen zadnjega poglavja razviti metodo, ki omogoča združitev mikroekonomskih in makroekonomskih stres testov, za kar doslej še ni bilo podanih inovativnih in splošno razširjenih konceptov.

TEORETIČNI OKVIR

Stres testi so lahko opredeljeni kot proces, za izvedbo katerega je potrebno narediti več korakov. Prvi med njimi obsega določitev pokritosti oziroma določitev velikosti vzorca in institucij. Pokritost stresne analize bi morala obsegati vse sistemske banke, torej tiste, ki so poglavitne za nemoteno delovanje bančnega sistema. Pogost kriterij, ki določa banko kot sistemsko, je velikost v smislu sredstev ali tržnega deleža. Prav tako je za stres teste pomembna izbira podatkov v smislu odločanja med uporabo mikroekonomskih in makroekonomskih podatkov. V tem kontekstu je moč ločiti med ″bottom-up″ in ″top-down″ pristopom. V prvem primeru je izvedba samih stres testov prepuščena individualnim bankam, kjer nadzorna institucija določi makroekonomske predpostavke za oblikovanje scenarija. Ker banke same izvajajo stres teste, le ti temeljijo na individualnih podatkih, kar omogoča zajetje specifik in večjo natančnost rezultatov, ki pa zaradi individualnih izvedb niso primerljivi med seboj. Nasprotno ″top-down″ pristop temelji na agregatnih podatkih in nadzorna institucija sama izvede stres test. Seštevanje podatkov povzroči izgubo specifikacij in nezmožnost prepoznavanja kanalov prenosa tveganja., vendar pa omogoča večjo primerljivost.

Naslednji korak obsega prepoznavanje tveganj. Tveganja so lahko kreditna, tržna, valutna, obrestna, tečajna in druga. Pomembnost posamezne vrste tveganja bo določena glede na dejavnost posameznega bančnega sistema. Kot primer bi lahko bilo rečeno, da bosta za izrazito mednarodno usmerjene bančne sisteme najbolj relevantna tečajno in tržno tveganje. Obravnavano magistrsko delo je osredotočeno na kreditno tveganje. Ko je posamezna vrsta tveganja prepoznana, je potrebno posamezne šoke, ki iz tega tveganja izhajajo, konstruirati v makroekonomskem scenariju. Tovrstni scenariji so običajno oblikovani z makroekonometričnimi modeli. Tovrstne modele je moč ločiti na strukturne modele, vektorsko avto-regresijske modele in čiste statistične modele. Strukturni modeli se nanašajo na notranje modele institucij, kot so centralne banke, in so namenjeni splošnim ekonomskim projekcijam. Pomembna lastnost strukturnih modelov je, da povezujejo ekonomsko teorijo in predpostavke z statističnimi in ekonometričnimi metodami. Nasprotno nestrukturirani modeli, kot so avto-regresijski modeli (VAR), omogočajo večjo fleksibilnost v smislu dodajanja spremenljivk in lažje interpretacije, vendar pa niso podprti z ekonomsko teorijo. To pomeni, da tovrstni modeli ne bodo najbolj ustrezni, če je primarni cilj stres testov zunanja komunikacija z namenom pojasnjevanja sistemskih tveganj. Tretja vrsta modelov temelji na čistih statističnih pristopih. V splošnem se je izkazalo, da je prednost zadnjih v tem, da omogočajo spremembe v korelaciji glede na krizno in normalno obdobje, kar pri VAR modelih ni mogoče, vendar pa je slabost v interpretaciji šokov in pojasnjevanju učinkov. Izbira same metode bo torej temeljila na že prej omenjenih ciljih.

Pri oblikovanju scenarija je prav tako pomembna določitev same verjetnosti scenarija. V tem pogledu ločimo dva pristopa: najslabši možni scenarij in scenarij z določitvijo praga oziroma katastrofalni scenarij. V prvem primeru je scenarij oblikovan na podlagi določitve njegove verjetnosti (npr. 1 %). Verjetnost temelji na zgodovinskih opazovanjih, kar predstavlja glavno omejitev tega pristopa. Predvideva namreč, da finančni sistemi ne bodo soočeni z večjimi strukturnimi spremembami. Tako se običajno izkaže, da so hipotetični scenariji bolj verjetni, kot se je to sprva domnevalo. Način oblikovanja scenarijev z določitvijo praga omogoča vpeljavo hipotetičnih scenarijev. V tem primeru se sprva določi prag ali velikost makroekonomskih šokov, ki postavijo finančne institucije pred bankrot, in šele nato verjetnost njegovega uresničenja. Od tod tudi ime katastrofalni scenarij.

Pregled metodologije in preteklih izkušenj je potrdil, da so najpogosteje uporabljene ekonomske spremenljivke: rast BDP, kratkoročna obrestna mera in nezaposlenost. Pri tem je pomembno poudariti, da makroekonomski modeli običajno ne vsebujejo finančnih spremenljivk, ki bi neposredno povezovale bilance stanj bank z makroekonomskim šokom. Tako so pogosto potrebni satelitski modeli, ki povežejo makroekonomske šoke z bančnimi spremenljivkami. V tem smislu ločimo modele, ki temeljijo na podatkih o kakovosti posojil in na podatkih o kakovostih posojilojemalcev. V prvem primeru makroekonomske spremenljivke povežemo s spremenljivkami, kot so: slaba posojila (″non-performing loans″), rezervacije (″loan loss provisions″), odpisi (″write-offs″) in drugi. Glavni problem tovrstnih modelov je ta, da so podatki o kakovosti posojil odložen indikator kakovosti sredstev ali z drugimi besedami, da izražajo pretekle šoke. Poleg tega se klasifikacija zgoraj omenjenih kategorij razlikuje med državami in različnimi pravnimi ureditvami. Nasprotno modeli, ki temelji na podatkih o individualnih kreditojemalcih, povezujejo verjetnost neplačil (″probability of default″) s karakteristikami posojilojemalcev, kot so npr.: poslovni dohodki, likvidnost, zadolženost, kreditne ocene in druge. Podlaga za ta pristop je Mertonov model, ki poveže tržne in makroekonomske spremenljivke z donosi na kapital podjetja. Ocenjeni donosi na kapital se nato uporabijo za izračun verjetnosti neplačil (PD). Prednost tovrstnih modelov je, da veliko prej zaznajo morebitne nevarnosti in so, ker temeljijo na individualnih podatkih o posojilojemalcih, veliko bolj natančni kot modeli, ki temeljijo na podatkih kakovosti portfelja. Mertonov tip modela lahko uvrstimo med strukturne modele (preučuje namreč strukturo bilanc podjetij), poznamo pa še nestrukturirane modele, ki temeljijo na podatkih o individualnih posojilojemalcih. Zadnji je uporabljen tudi v stres testih Banke Slovenije.

Značilnost nestrukturiranih modelov, ki temeljijo na podatkih o posojilojemalcih, je ta da preučujejo migracije klientov bank med različnimi kreditnimi ocenami. Tako so v analizah kreditnih tveganj, podanih s strani Banke Slovenije, posojilojemalci razporejeni v pet kakovostnih razredov (od A do E) glede na njihovo finančno stanje in zmožnost odplačevanja obveznosti. Prehajanje med razredi je prikazano s tako imenovanimi kreditnimi matrikami. Stres je impliciran skozi šok, ki opredeljuje kratkoročno zadolženost posojilojemalcev, in skozi likvidnostni šok (šok v smislu dohodka na prodano enoto). Rezultati kažejo, da je likvidnostni šok bolj značilen in ima večji učinek na kreditno tveganje kot zadolženost. Prav tako Banka Slovenije ugotavlja prociklično obnašanje slovenskih bank. Za banke v Sloveniji je namreč značilno, da v dobrih gospodarskih časih ocenjujejo svoje kliente veliko bolj optimistično, čeprav se njihovo stanje v kriznih časih ne razlikuje bistveno.

Evropska Bančna Agencija (EBA) ocenjuje finančno stabilnost EU držav v okviru ″top-down″ pristopa. Predpostavke glede makroekonomskega scenarija so določene s strani Evropske Bančne Agencije, medtem ko je njihova implementacija prepuščena posameznim bankam. Banke nato posredujejo metodologijo in rezultate nacionalnim centralnim bankam, ki zagotavljajo kakovost s pomočjo primerjalnih rezultatov, zagotovljenih s strani ECB v okviru ″top-down″ pristopa.

Kljub očitnemu napredku v metodologiji pa mnogi izzivi in problemi ostajajo. Eden takih je zagotovo pomanjkanje podatkov oziroma kratke časovne vrste, ki ne zajemajo dovolj ekstremnih dogodkov, ki bi zagotavljali ustreznost stresne analize. Vsaka nova kriza prinese s seboj scenarije, ki so do tedaj veljali za malo verjetne in nerealne. Pomanjkanje podatkov prav tako poveča velikost napake, ki se v primeru uporabe satelitskih modelov zgolj še poveča, saj ocene prenašamo med modeli. Možne rešitve na tem področju so uporaba neagregiranih podatkov v kar se da največji meri možno, panelne analize, uporaba hipotetičnih scenarijev (npr. katastrofalni scenarij) in druge.

Naslednji problem, ki pesti stresno analizo, se nanaša na vključitev endogenih odzivov na stresno situacijo. Zelo malo verjetno je pričakovati pasivni odziv agentov, ki bi pomenil njihovo statičnost v smislu sprejemanj prvotne alokacije portfelja brez poskusov, da bi kompenzirali naraščajoče izgube. Endogen odziv je možno pričakovati tudi s strani nadzornih institucij in centralnih bank v smislu uravnavanja obrestnih mer in drugih vzvodov. Endogenost se lahko odrazi tudi v povratnih makroekonomskih učinkih, kot je npr. kreditni krč in posledično padec gospodarske aktivnosti. Tovrstni endogeni odzivi ostajajo prezrti s strani večine stres testov, opravljenih v preteklih letih.

Izziv prav tako ostaja vključitev nelinearnosti v model. Večina današnjih metod namreč domneva konstantna razmerja, kar pa morda ni realno pričakovati v kriznih situacijah. Tu obstaja potencial, da se ta razmerja in vzročnosti spremenijo. Pogosto so prav nelinearnosti posledica endogenih odzivov, ki spremenijo ustaljena razmerja v obdobju normalnega delovanja. Kljub temu predpostavka o nelinearnosti morda le ni tako moteča, še posebej, če je cilj stres testov zgolj komunikacija, kjer upoštevanje nelinearnosti ne bi prineslo dodatnih informacij o transmisiji šoka, le večje ocenjene vrednosti.

Prav tako so v analizah pogosto uporabljene distribucije, ki ne ustrezajo realnim stanjem. Predpostavke in uporaba normalnih distribucij lahko privede do podcenjevanja drastičnosti in frekvence stresnega dogodka. Tako je pomembno prepoznavanje distribucije z večjimi repnimi vrednostmi, ki domneva večjo verjetnost ekstremnega dogodka.

STRES TESTI PODJETNIŠKIH KREDITNIH PORTFELJEV V EVROPSKIH BANČNIH SISTEMIH

Namen tega poglavja je bila demonstracija večstopenjskega procesa stres analize, opisanega v prvem delu. Stres test je bil izveden na primeru naslednjih držav: Italija, Grčija, Portugalska, Španija, Belgija, Francija, Nemčija in Finska. Države niso bile izbrane naključne, temveč z namenom ugotavljanja razlik med državami za katere velja splošno prepričanje, da se težje soočajo z obstoječo krizo v primerjavi z državami, ki veljajo za merilo uspešnosti. Ker je namen bilo prikazati aplikacijo več faznega proces stres testov, sem svojo analizo razdelil na tri dele. V prvem delu konstruiram makroekonomski model z namenom oblikovanja stresnega scenarija, v drugem delu ocenjene stresne napovedi za makroekonomske spremenljivke povežem s stresnim modelom s stopnjo odpisov kreditov za vsako posamezno državo, medtem ko v tretjem delu dobljene rezultate interpretiram z izračunom kapitalizacije za vsako posamezno državo.

Makroekonomski šok scenarij temelji na 3 spremenljivkah, in sicer: rasti BDP-ja, stopnji nezaposlenosti in kratkoročni obrestni meri. Spremenljivke so bile izbrane na podlagi literature in prvega poglavja, kjer so omenjene 3 spremenljivke, najpogosteje zastopane pri preteklih analizah. Poleg tega analiza temelji na stres testih za posamezne države, kar pomeni, da te tri spremenljivke predstavljajo največjo primerljivost med pridobljenimi ocenami modela za posamezne države. Spremenljivke, kot je npr. izvoz, držav ne bi postavljale na isto raven, saj so nekatere države morda bolj izvozno orientirane kot druge in podobno. Scenarij je oblikovan kot multivariatna šok analiza, kar pomeni, da so vse tri spremenljivke in šok v njih, obravnavane simultano. V ta namen je bil uporabljen Vektorsko Avtoregresijski model, ki vse tri spremenljivke obravnava kot endogene. V prvem koraku so bila vzpostavljena razmerja med spremenljivkami, medtem ko so v drugem koraku bila ta razmerja uporabljena za napoved vrednosti s pomočjo rekurzivnosti. Napovedi so bile podane za 8 četrtletij (do vključno z zadnjim četrtletjem 2012) naprej od zadnjega razpoložljivega podatka (zadnje četrtletja 2010). Da bi bil scenarij v skladu s predpostavko o *ekstremnem, a še verjetnem* dogodku, so bile kot šok izbrane skrajne vrednosti na 99 % intervalu zaupanja. V primeru spremenljivke BDP je bila izbrana spodnja meja, medtem ko je bila za spremenljivki obrestna mera in stopnja nezaposlenosti izbrana zgornja meja. Najhujše prognoze so bile podane za Španijo in Grčijo, medtem ko je bil najmanjši šok predviden v primeru Nemčije.

V drugem delu so makroekonomske spremenljivke povezane z stopnjo odpisov (″writte-offs″) posojil nefinančnim podjetjem. Magistrska naloga je osredotočena zgolj na posojila nefinančnim podjetjem, saj literatura kaže, da odzivnost drugih kreditov (hipotekarni, potrošniški) ni enaka, kakor tudi ni enako njihovo razmerje z makroekonomskimi spremenljivkami. Satelitski model prav tako temelji na VAR metodi, vendar pa je v tem primeru vektor makroekonomskih spremenljivk nastopa kot eksogen del modela, medtem ko so odpisi endogena spremenljivka. V vseh ocenjenih primerih so korelacije pričakovane, torej negativna korelacija med BDP in odpisi ter pozitivna korelacija med odpisi in preostalima dvema makroekonomskima spremenljivkama. V prvem delu so vzpostavljena razmerja med odpisi in makroekonomskimi spremenljivkami na podlagi opazovanih podatkov (do konca leta 2010). V drugem delu je model kalibriran s prihodnjimi makroekonomskimi šoki za potrebe napovedi bodočih odpisov. Ocenjene vrednosti bodočih odpisov ne morejo potrditi prvotne hipoteze, da so bančni sistemi držav v težavah bolj dovzetni za makroekonomske šoke. Še več, največja raven odpisov je bila ocenjena za

Nemčijo, ki pa je ob enem imela najbolj blage ocene ekstremnega šoka. V celoti so ocene odpisov precej skladne z ocenami stres testa Evropske Bančne Agencije za leto 2011, ki v povprečju napovedujejo stopnjo odpisov 2,5 % ob koncu leta 2012.

Ocenjene vrednosti so bile uporabljene za izračun kapitalske ustreznosti posameznih držav. Kapitalska ustreznost je bila ocenjena na podlagi Tier 1 kapitala. Ocenjen prag kapitalske ustreznosti je bil postavljen na 5 %, skladno s stres testom Evropske Bančne Agencije. Nobena izmed držav ne pade pod postavljen prag. Relativno najslabše kapitalsko stanje v letu 2012 izkazuje Portugalska s 5,2 %. Ocene kapitalske ustreznosti so skladne z ocenami, podanimi s strani Evropske Bančne Agencije. Edine večje deviacije je bilo moč zaznati v primeru Grčije, kjer ocene pridobljene v nalogi očitno podcenjujejo učinke makroekonomskih učinkov na bančni sistem. To je lahko deloma pojasnjeno s tem, da kreditno tveganje v grškem bančnem sistemu ne predstavlja ključnega dejavnika, ampak bi morda bilo vredno upoštevati ostale vrste izpostavljenosti (lastniški kapital, državne obveznice).

SLOVENSKI BANČNI SISTEM

Namen poglavja je opredeliti bankam-specifične spremenljivke, ki bi lahko služile kot zgodnji opozorilni signal stabilnosti bančnega sistema. V tem smislu je poudarek na določanju determinant slabih kreditov in njihovemu odzivu na šoke v teh spremenljivkah. Prav tako je namen poglavja ponuditi metodo, ki omogoča združitev ″*top-down*″ in ″*bottom-up*″ pristopa.

Prvi del poglavja je namenjen povzetju splošnega stanja slovenskega bančnega sistema. Kreditna aktivnost v Sloveniji stagnira že od leta 2009 dalje ob enem pa se je struktura portfelja neprestano poslabševala. Posebej zaskrbljujoče je dejstvo, da slovenska podjetja, ki dobro poslujejo, iščejo vire financiranja v tujini, kar pomeni, da slovenske banke izgubljajo priložnosti za nove vire dohodkov in izboljšanje strukture kreditnega portfelja. Najslabša struktura portfelja je bila zaznana v nefinančnem podjetniškem sektorju, kar je predvsem posledica propadov velikih gradbenih podjetij v Sloveniji. Prav do teh podjetij imajo največje državne banke najvišjo izpostavljenost. Stanje tujih in manjših domačih bank je boljše, struktura kreditnega portfelja se celo izboljšuje.

Kot sem že omenil, me v lastni analizi zanimajo bankam-specifične determinante slabih kreditov (zamude nad 90 dni). Bankam-specifične spremenljivke je moč razdeliti v kategorije, ki odražajo politike posameznih bank: upravljanje, moralni hazard, prociklična kreditna politika in velikost.

Področje upravljanja opredeljuje spremenljivka ROA (″return on assets″) ali dohodek na sredstva. Negativna korelacija s slabimi krediti je bila pričakovana, kar pomeni, da bi se politike, ki stremijo k maksimizaciji dobička, morale odraziti v ostrejših pogojih kreditiranja in zato manjših slabih kreditih. Vendar pa literatura tu ni enoznačna, saj naj bi predvsem v razvijajočih državah pritiski po ustvarjanju dobička privedli do bolj tveganih posojilnih politik. Poleg tega je kot najbolj izpostavljeno orodje bank v analizi uporabljena tudi obrestna mera, za katero je bila postavljena hipoteza pozitivne korelacije s slabimi krediti.

Moralni hazard bank je najbolje opredeljen s spremenljivko LtD (″loan to deposit″) ali razmerje kreditov glede na depozite. To razmerje pojasnjuje moralni hazard s stališča, da povečanje kreditov, ki niso kriti z depoziti, odraža politiko doseganja trenutnih začasnih dohodkov na račun povečanja slabih kreditov v prihodnosti. Tako je moč pričakovati pozitiven vpliv te spremenljivke na povečanje slabih kreditov.

Prociklična politika banke je izražena skozi ekspanzivno posojilno politiko v dobrih časih, ki neposredno razširi bančni portfelj na slabše kreditojemalce. Tako je pozitivna korelacija z odpisi pričakovana. Prav tako je predpostavljeno, da je velikost banke lahko dobra determinanta slabih kreditov, kjer bi načeloma večja tržna moč (krediti individualne banke glede na celotne kredite) morala zmanjšati slabe kredite, torej negativna korelacija. Vendar pa, kot se izkaže, je gibanje tržne moči precej poravnano z gibanjem rasti kreditov in zato ne nudi dodatne pojasnjevalne moči.

Poleg opredeljenih bankam-specifičnih spremenljivk je bila v model vključena tudi spremenljivka BDP kot primerjalna makroekonomska spremenljivka. Razmerja in učinki posameznih spremenljivk so ocenjeni z uporabo panelnega VAR modela. To pomeni, da se vse vključene spremenljivke navezujejo na četrtletne panelne podatke, in sicer na podatke za 8 največjih bank v slovenskem bančnem sistemu in za obdobje od 2006 do 2011. Panelni var omogoča uporabo dezagregiranih podatkov in na ta način natančnejšo določitev posameznih korelacij. Vse spremenljivke vstopajo v model kot endogene, šoki in učinki na slabe kredite pa so implicirani z impulznimi odzivi. V tem kontekstu uporaba satelitskih modelov torej ni potrebna. Prav tako pa impulzni odzivi omogočajo upoštevanje povratnih učinkov (″*feedback effects*″).

Ocenjeni koeficienti za ROA spremenljivko potrjujejo hipotezo slabega upravljanja. Zmanjšani dohodki banke so torej dober pokazatelj kvalitete bančnega upravljanja, pri čemer je mišljeno predvsem odobravanje kreditov in ocena posojilojemalcev. Spremenljivka najmočnejšo pojasnjevalno moč izkazuje v tretjem odlogu. Bolj natančno to pomeni, da se bo znižanje dohodkov za 1 odstotno točko odrazilo v zvišanju slabih posojil za približno 1,087 odstotne točke tri obdobja v prihodnosti. Povečanje obrestne mere, ki prav tako sodi v kategorijo upravljanja banke, ima na dolgi rok pričakovan pozitiven vpliv na povečanje slabih kreditov.

Za najmočnejšo in najbolj značilno se je izkazala spremenljivka, ki odraža moralni hazard. Ta rezultat nakazuje na slovenski bančni sistem kot na prostor s prisotnimi spodbudami za moralno hazardiranje. Nasprotno prociklična kreditna dejavnost nima statistično značilnega vpliva na slabe kredite, prav tako pa so ocenjene korelacije v nasprotju z začetnimi postavljenimi hipotezami. Tako je moč sklepati, da vsako ekspanzivno večanje kreditov še ne pomeni brezbrižno prevzemanje tveganj. Sodeč po tem je mogoče spremenljivko LtD razumeti kot močnejši kratkoročni indikator slabih kreditov. Samo povečana posojila v tem smislu torej izražajo zgolj dolgoročne učinke (3 do 4 leta). Razlaga za tovrstno nepričakovano negativno korelacijo je ta, da na kratek rok kreditna rast sovpada z gospodarsko aktivnostjo, kar pomeni, da krediti rastejo, ko imajo podjetja redne in zadostne dohodke. Nasprotno v kriznih časih, ko je vsesplošno zaupanje ekonomskih agentov nizko, je pri bankah prav tako moč opaziti bolj konzervativne politike, pri čemer se pa obstoječ portfelj odraža v vedno slabših kreditih. Tako se vsaj na kratek rok vzpostavi negativna korelacija, ki nedvomno vpliva na dobljene rezultate. To potrjujejo tudi rezultati pridobljeni za makroekonomsko spremenljivko BDP, ki na kratek rok izkazuje značilno in s pričakovanji skladno korelacijo. V tem pogledu so makroekonomski indikatorji še vedno boljši pokazatelj slabih kreditov, kot je npr. bankam specifična rast kreditov.

Če je vpliv kreditov na slabe kredite neskladen s pričakovanji na kratek rok, tega vsekakor ni moč trditi za povratne učinke. Izkaže se namreč, da poslabšanje kreditnega portfelja nemudoma upočasni rast samih kreditov. To potrjuje, da je endogeni odziv bank močan in da ni moč pričakovati pasivnega odziva bank ter nadaljevanja pred kriznih politik. Prav tako so bili zaznani močni povratni učinki poslabšanja kreditnih portfeljev na gospodarsko rast. Slednje je predvsem posledica močnega nezaupanja bank v kriznih časih, ki lahko ne nazadnje pripelje do kreditnega krča, ki se odrazi v znižani gospodarski rasti.

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