Charles University in Prague
Faculty of Social Sciences
Institute of Economic Studies

Master's Thesis

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Macroeconomic stress-testing of banking systems: survey of methodologies and empirical application

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Abstract

This thesis deals with stress testing as a process that helps to assess the impact of potential adverse shocks on the soundness of a financial system. First section is dedicated to non-technical discussion about stress testing and to some methodological issues. The main focus lies on the system-wide macroeconomic stress testing.

The empirical part of the thesis is a contribution to macroprudential analysis of the quality of the aggregate loan portfolio in the Czech Republic. This study adopts a vector autoregression model applied to the Czech banking sector in order to judge its stability and present some evidence on macroeconomic variables affecting the Czech banking system. As a measure of the strength of the loan portfolio is used the stock of non-performing loans vis-à-vis total loans in the sector. The thesis follows the widely used methodology and seeks to identify significant macroeconomic risk factors affecting the loan portfolio quality. The latter part aims also to forecast the most likely development of the loan portfolio.

Abstrakt

Diplomová práce se zabývá zátěžovým testováním jakožto nástrojem, který přispívá k ohodnocení odolnosti finančního systému vůči nepříznivým šokům. První část práce je věnována netechnickému shrnutí procesu zátěžového testování. Teoretická část diplomové práce rozlišuje mezi zátěžovým testováním na úrovni jednotlivých bank a na agregované úrovni a shrnuje jednotlivé aspekty a atributy procesu zátěžového testování. Hlavní pozornost je soustředěna především na zátěžové testování celého systému prováděné na agregovaných datech.

Empirická část diplomové práce je praktickou aplikací modelu vektorové autoregrese na agregovaná data českého bankovního sektoru. Jakožto míra stability agregovaného úvěrového portfolio je použit poměr úvěrů v selhání na celkově poskytnutých úvěrech. Diplomová práce využívá obecně používaných analytických nástrojů vektorové autoregrese za účelem identifikace významných makroekonomických faktorů ovlivňující kvalitu portfolia bankovních úvěrů. Součástí empirické analýzy je taktéž předpověď vývoje kvality úvěrového portfolio.

Keywords

Stress testing, financial stability, vector autoregression, non-performing loans, macro-prudential analysis, Czech Republic

Klíčová slova

Zátěžové testování, finanční stabilita, vektorová autoregrese, úvěry v selhání, makroprudenční analýza, Česká republika

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Prohlášení:

Prohlašuji, že jsem diplomovou práci vypracovala samostatně s použitím uvedené literatury a pramenů. Prohlašuji, že práce nebyla použita k získání jiného titulu. Souhlasím, aby diplomová práce byla zpřístupněna pro studijní a výzkumné účely.

Declaration:

The author hereby declares that she compiled this thesis independently, using only listed resources and literature in the bibliography.

The author also declares the master's thesis was not published prior to submission and was not used to obtain another academic degree.

The author grants to the Charles University in Prague permission to publish the master's thesis online for academic purposes.

V Praze dne / In Prague, 18.5.2011

Jana Šimečková

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Master's Thesis Proposal

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Proposed Topic:

Macroeconomic stress-testing of banking systems: survey of methodologies and empirical application

Topic Characteristics:

Assessing financial stability has been an issue of rapidly growing importance to central banks and other banking authorities in the recent decades. Stress testing aims to assess the impact of potential (abnormal) shocks on the soundness of a financial system by applying them to a model of the system in order to assess the vulnerability of the portfolio to the abnormal shocks and/or market conditions.

The theoretical part of the master's thesis will indentify various techniques to assess the vulnerabilities of the financial system. Based on the available literature, the theoretical part of the thesis will summarize the key stress testing techniques used in the central banks and/or other institutions and authorities. The aim is to review the quantitative methods developed at selected authorities for stress testing credit risk with particular focus on macroeconomic stress test techniques. The theoretical part will therefore provide a survey on authorities approaches based on number of recent papers published by central banks and supervisors.

The empirical part of the thesis will concentrate on the application of modeling the credit risk using macroeconomic explanatory variables to actual data. The aim of the thesis is (1) to find a relationship between selected common indicators of credit risk and some other macroeconomic variables, (2) quantify the impact of those macroeconomic variables and (3) provide an estimate of the sensitivity to the relevant risk factors.

Hypotheses:

The empirical part of the thesis will answer following questions:

1. Indentify significant risk factors; to what extend does the credit risk depend on the macroeconomic variables
2. Identify and evaluate the impact of the changes in the macroeconomic variables on the indicator of credit risk
3. Does aggregate stress testing model provide correct estimate of the impact of the crisis on the banking system?

Methodology:
The data for the empirical part of the thesis will be obtained through the publicly available databases, such as CNB – ARAD, IMF International Financial Statistics and Fitch's BankScope database.

The analysis of the obtained data will be done using standard econometric methods. In order to identify significant risk factor the author will follow the standard approach of univariate OLS regression of the credit risk indicator on the comprehensive data set of macroeconomic variables. Having obtained the significant macroeconomic variables, the author intends to use the VAR approach to analyze the predicted relationship between the credit risk indicator and the macroeconomic variables. All econometric operations will be conducted via appropriate and to the author available statistical software.

Outline:

1. Introduction
2. General framework of stress testing – widely used concepts and techniques of stress testing, its imperfections and pitfalls
3. The survey of authorities approaches of stress testing
4. Credit risk stress testing
5. Empirical part – development of credit market, macro stress test model
6. Conclusion

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List of Abbreviations

ACF	Autocorrelation function
ADF	Augmented Dickey-Fuller test
AIC	Akaike's Information Criterion
BIC	Schwarz Bayesian Criterion
BCBS	Basel Committee on Banking Supervision
CAR	Capital adequacy ratio
CGFS	Committee on the Global Financial Systems
CNB	Czech National Bank
CPI	Consumer price index
CSU	Czech Statistical Office
EU	European Union
FEVD	Forecast error variance decomposition
FSAP	Financial Sector Assessment Program
FSIs	Financial Soundness Indicators
FX	Foreign exchange
GDP	Gross domestic product
HQ	Hannah-Quinn Criterion
IMF	International Monetary Fund
KPSS	Kwitlowski, Phillips, Schmidt, and Shin test
LLPs	Loan loss provisions
LTCM	Long Term Capital Management
NPLs	Non-performing loans
OLS	Ordinary least squares
PRIBOR	Prague Interbank Offered Rate
VaR	Value-at-risk
VAR	Vector autoregression
VECM	Vector error correction model

1 Introduction

The recent financial crisis highlighted the importance to monitor the stability of the financial system and to develop further analytical tools to measure the systemic risk of the financial system. Especially, financial stability of the system and its ability to withstand unanticipated shocks has become the centre of attention of various supervisory bodies as well as policymakers in recent years. The recent crisis has shown the vulnerability of the financial system doesn't have to stem only from endogenous factors but also as the consequence of adverse development of the macroeconomic and financial environment. Since any instability in the financial and macroeconomic environment can potentially has a substantial impact on functioning of the financial system, which in turn could affect the real economy and therefore imply second-round effects on the financial system, the necessity of finding a way how to understand the risks in the system, and hence reduce the likelihood of occurrence and the impact of the potential adverse shock, has been of utmost concern.

Even thought there is a wide consensus among central bankers about the importance to control the impact of financial innovations and macroeconomic fluctuations on the financial system, there is no widely accepted or used uniform model or analytical framework for assessing and measuring financial stability. However, stress testing is one of the analytical tools and methods that helps monitor, identify and anticipate the potential vulnerabilities in the examined system. Stress tests applied on the aggregated level usually focus on various multiple risks and contagion channels in the system. However, credit risk remains still one of the most important risks in the financial system.

The healthiness of the banking sector lies in the quality of its aggregate loan portfolio. As a measure of the strength of the loan portfolio is usually considered the stock of non-performing loans vis-à-vis total loans in the sector. The Czech Republic has been traditionally viewed as an example of a bank-oriented financial system and hence the quality of the aggregate loan portfolio of the Czech commercial banks represents a key indicator of financial vulnerability.

The principal aim of this thesis is to quantify the effects of macroeconomic performance on the banking sector's loan portfolio quality in the Czech Republic. The thesis represents an application of the vector autoregression methodology on the Czech banking sector in order to assess its sensitivity towards various macroeconomic factors. The thesis follows the widely used methodology and seeks to identify significant macroeconomic risk factors affecting the loan portfolio quality. Furthermore, the thesis attempts to identify and evaluate the impact of changes in the macroeconomic variables on the growth of non-performing loans as an indicator of credit risk.

The thesis is organized as follows: First chapter specifies the stress testing procedure and its general properties. It distinguishes between stress tests run on portfolio basis and stress tests conducted on the aggregate level, i.e. the system-wide stress test, and provides a comprehensive comparison of major differences in the definition and aim of stress testing applied to the different levels. First chapter also aims to list reasons for usage of stress test and limitations of applying stress testing procedure on the system-wide basis.

Second chapter of the thesis describes the development in the Czech banking sector over the period from 2002 to 2010. Since the credit market and hence the quality of the loan portfolio is assumed to be connected to the overall development of the macroeconomic conditions of the country, first part of the second chapter summarized the macroeconomic performance of the Czech Republic over the mentioned time period. The remaining is devoted to development on the Czech credit market, its major exposures and assessment of the current condition of the loan portfolio quality.

Third chapter of the thesis reviews literature and some recent work conducted on the relationship between the development of non-performing loans and various macroeconomic factors. This part summarizes empirical findings that have been presented in the literature.

Last chapter represents the major focus of the thesis – the empirical application of the vector autoregression methodology on the Czech banking sector. In the first part, the significant macroeconomic risk factors and their expected relation towards credit risk indicator – the NPL ratio – is described and the following part focuses on the empirical application itself. The latter part also aims to forecast the most likely development of the loan portfolio and assesses the loan portfolio quality.

2 General properties of stress tests

2.1 Stress testing definition

The call for stress testing of the financial institutions within the European Union is recorded in the New Basel Capital Accord (also known as Basel II), that emphasizes the importance of the new capital adequacy framework.[1] The final document that includes all the requirements on the implementation of the new capital adequacy framework, together with the guidance on the encouraged monitoring and risk-management practices, was issued in 2006. The implementation of the new framework took effect in the member states of the European Union.

The New Basel Capital Accord requires the banks to conduct stress testing procedures with regard to credit risk:[2]

"…bank must have in place sound stress testing processes for use in the assessment of capital adequacy. Stress testing must involve identifying possible events or future changes in economic conditions that could have unfavourable effects on a bank's credit exposures and assessment of the bank's ability to withstand such changes." (Basel Committee on Banking Supervision [BCBS], 2006, para. 343)

Despite the fact, that the New Basel Capital Accord does not exactly define or specify in the body of the document what constitutes the stress testing, the above could be seen as a broad definition of stress testing.

Academic papers and working papers produced by the supervisory bodies usually distinguish between stress test run on the particular portfolio of the individual financial institution and a system-wide stress test, and thus - in that sense - the definitions slightly vary.

As far as the individual financial institutions (such as individual banks or companies) are concerned, Jones *et al.* (2004) define stress test as a set of analytical techniques that are

[1] The exhaustive description of the three pillar structure of the New Basel Capital Accord as well as the monitoring and risk management framework under the particular pillars can be found in BCBS (2005) and BCBS (2006). The key elements of the Basel II Accord are summarized for example in BCBS (2003).

[2] The New Basel Capital Accord requires the financial institutions to conduct stress tests with regard to credit risk (para. 343), liquidity risk in relation to collateral (para. 158) and market risk (para. 718).

used in order to obtain a numerical estimate or some sort of measurement of the sensitivity of a portfolio to a set of extreme but plausible shocks.

Similar definition can be found in Blaschke *et al.* (2001), where the stress test at the portfolio level is defined as 'range of techniques that attempt to identify the vulnerability of the portfolio to adverse changes in the macroeconomic environment or to exceptional, but still possible, events'.

Generally speaking, the major difference between the portfolio level and system-wide stress testing lies within the underlying portfolio examined. Since the basis of stress testing comes from the methods that banks and companies use to manage market risk of their portfolios and trading books, the objective of stress tests is to make the risk connected with the portfolio more transparent and provide an estimate of the effect of shocks that could occur to the company's portfolio. Over the time, the stress testing techniques have been applied in much boarder context, namely to selected groups of institutions or the entire financial system in order to assess the threats to the financial system. However, as pointed out by Jones *et al.* (2004), the system-wide stress tests are still applied only to a selected subset of institutions, typically to selected group of banks.

According to Quagliariello (2009) system level stress testing process is a process involving quantitative tools to assess the soundness of the financial system under the extreme, but plausible, events.

Again, similar definitions can be found in various financial literature and working papers of the supervisory bodies. Čihák (2007) speaks in general about stress testing as a set of 'various techniques for assessing resilience to extreme events'. Since stress tests aim to go beyond standard operational capacity of the system – usually up to the breakeven point – observed results are used in order to determine the stability of the given system.

2.2 Stress testing on the portfolio level vs. system focused stress testing

As noted in the previous section, stress testing is one of the analytical tools and methods that help monitor, identify and anticipate the potential vulnerabilities in the examined system. Stress testing can be applied to a trading book and/or a loan book of an individual company/bank as part of their risk management practices or to the whole financial system as part of the stability assessment conducted nowadays by many central banks.

Figure 1: Stress testing at a portfolio level and at the aggregate level

	Stress Testing at the Portfolio Level	Stress Testing at the Aggregate Level
Aim	- risk management tool used to evaluate the potential impact on a firm by movement of a specific risk factor and/or set of financial variables - provides understanding of the latent risk to a trading book from extreme movements - stress testing used as a complement to risk management methods (such as value-at-risk)	- evaluation of the vulnerabilities of the financial system or selected subset of institutions - the whole system (significant part of the system) is subject to the adverse events
User	- individual banks, firms, practitioners and risk managers	- supervisory authorities (central banks), institutions
Risks	- market risk, interest rate risk, credit risk, operational risk	- various types of risk: market risk, credit risk, liquidity risk, interest rate risk, exchange rate risk, contagious risk etc.
Attributes	- applied usually to trading books of the firm as marketable instruments that are easily marked-to-market - stress testing often used as a complement to statistical risk management techniques (such as value-at-risk)	- more macroeconomic in nature - contributes to better understanding of the link between the financial sector and the economy

Figure 1 provides comparison of major differences in the definition and aim of stress testing applied to individual portfolios and at the aggregate level.

At the **portfolio level**, stress testing usually serves as a complementary method to the statistical risk management tools (such as value-at-risk or extreme value theory). Its aim is to capture the information not captured by those methods, mainly the information about behaviour of the portfolio under exceptional circumstances. As mentioned in Blaschke *et al.* (2001), stress testing often helps to determine if return on a particular product (in particular product line of the firm) is commensurate with adequate level of risk. Stress testing at the portfolio level is usually used to access market risk, but can focus on other risk or on multiple risks as well.

On the **aggregate level**, the stress testing exercise is usually conducted by the supervisory bodies (such as central banks) and other institutions[3] in order to assess the resilience of the country's financial system to adverse events and its ability to absorb potential exogenous shocks (Quagliariello, 2009). The ability to withstand adverse shocks to the economy goes hand in hand with the fragility of the financial system, the more fragile the financial system, the more severe the effect of a shock. Therefore, in order to evaluate the vulnerabilities of the system and its ability to withstand adverse events, the evaluation of the linkages between macroeconomic conditions and the financial system plays a crucial role.

On the contrary to stress testing used on a portfolio level, the aggregate stress testing exercise usually focuses on multiple risks. In fact, each country's central bank can identify different fields of potential vulnerabilities of the system (depending on many factors) and therefore also the stress testing models usually concentrate more on country-specific risk factors. According to Melecky and Podpiera's (2010) survey that focused on stress testing practices applied by the central banks of Central and South Eastern Europe, the major risk factor assessed was credit risk. In addition, majority of the models applied by the central banks incorporates market risk. Liquidity risk was performed by approx. half of the central banks and the contagion risk analysis by quarter of the examined central banks.[4] The relatively low focus of the central banks of the Central and South Eastern Europe region on the liquidity risk and contagion risk might be caused mainly due to relatively high complexity of computation and incorporation of those risks in the stress testing models. Another factor that limits the evolvement of models incorporating more risk factor lies within the data availability constraint.

2.2.1 Value-at-risk and stress testing

The basis for stress testing originally came from the risk management methods applied by individual companies and/or banks to manage risks of their trading books. The primary tool among the risk management techniques applied in order to evaluate risk exposure of the financial institution is computation of the value-at risk (VaR).

[3] For example The Financial Sector Assessment Program exists as a joint program of The World Bank and IMF concentrating on the in-depth analysis of a country's financial sectors. The financial stability assessment part of the FSAP program includes a macroeconomic stress testing exercise.

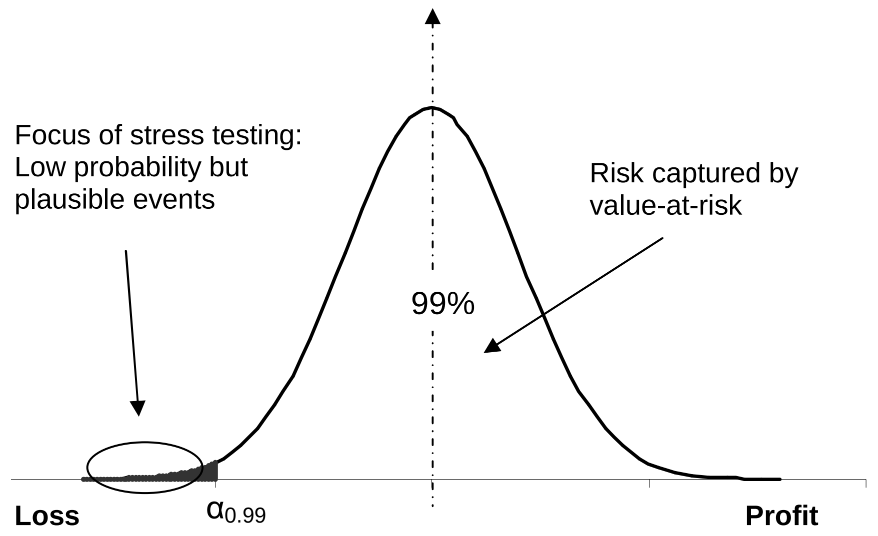
[4] Credit risk was the main risk factor of the central banks in the Central and South Eastern Europe. The credit analysis was performed by all 16 central banks, however, the techniques of the examination varied. Market risk was examined by 14 out of 16 central banks involved in the survey. 10 central banks focused on the liquidity risk and only 4 central banks involve the contagion risk analysis into their stress testing exercise.

Value-at-risk was first used in the 1980s by financial firms to measure risk exposure of their trading books. Since the late 1980s, use of VaR has expanded significantly. Nowadays, the value-at-risk analysis is conducted basically in every entity to measure its risk exposure, most often, however, still by commercial and investment banks to capture the potential loss in value of their portfolio.

In its most general form, value-at-risk is a statistical method, that measures the potential loss in a value of a portfolio or risky asset over a given time period and at a defined confidence level. Saying that a portfolio has a 1-year VaR of \$ X at a confidence level of 99% means that there is only 1% chance that – whatever happens – the portfolio will realize a loss greater than \$ X for that year. Value-at-risk is aggregate measure of market risk, it allows the risk managers to compute a general measure of economic loss that can equate the risks of different products and hence aggregate the risk on portfolio basis.

Popularity of value-at-risk analysis lies within its easy implementation – once understood the statistical measures, the concept of VaR is quite straightforward. Also, VaR can be computed for various time horizons (ranging from 1-day to 1-month time horizon) and confidence level (usually computed for range between 90% - 99% confidence level).

Figure 2: Value-at-risk and stress testing capturing the exceptional events



Source: adapted from CGFS (2005)

However, value-at-risk measures the possible loss in value of a portfolio arising due to “normal” market movements, i.e. losses greater than the value-at-risk is realized only with low probability. On the contrary, stress testing identifies the risks arising from abnormal market events, i.e. those that are typically not captured by the value-at-risk framework. Based on the above, stress testing is an efficient complementary method to value-at-risk in the attempt to understand the risk profile of a portfolio or on the aggregate basis. Figure 2 graphically shows the cooperation of value-at-risk and stress testing in risk management.

Other limitation of value-at-risk method is that VaR usually assumes that the risk factor or parameter is normally distributed while financial time series are in fact often characterized by fat-tail distributions (Kalirai and Scheicher, 2002; Babouček and Jančar, 2008). This could lead to a misinterpretation of the likelihood of the extreme events, since value-at-risk uses normal distribution loss function. Hence stress test can be effectively used in order to quantify the impact of the risks associated with fat tails. However, as mentioned in Kalirai and Scheicher (2002) stress test does not assign any probability to the likelihood of the extreme event’s associated loss occurring. It is rather a what-if analysis – in more structured and sophisticated way – that evaluates the impact of such an event on the portfolio.

2.2.2 Top-down vs. bottom-up approach

The coverage of stress testing expanded far beyond the evaluation of marketable instruments and trading portfolios. Central bankers and authoritative bodies on financial institutions are interested in conducting the aggregate stress tests of the whole system in order to obtain and evaluate the vulnerabilities of the financial system to potential risks. The focus of central banks and supervisory authorities lies therefore not on the particular portfolio or one financial institution, but rather on the entire financial system.

Nevertheless, aggregate stress tests face number of methodological issues. The most basic methodological issue is defining the appropriate approach how to quantify the aggregate impact of a shock on individual portfolios (Quagliariello, 2009). When talking about stress tests on the aggregate level, there are two main approaches used by the supervisory bodies – the top-down and the bottom-up approach.[5]

[5] See for example Quagliariello (2009), Kalirai and Scheicher (2002), Melecky and Podpiera (2010) or Jones *et al.* (2004) for further details and discussion.

Figure 3: Top-down and bottom-up approach

	Top-down	Bottom-up
Description of the approach	- collection and aggregation of balance sheet data from individual financial institutions - conduct stress test exercise on the aggregated data	- collection and usage of individual stress tests conducted by financial institutions - adding up obtained results from the individual participating financial institutions
Type	- macroprudential stress test	- microprudential stress test
Requirements	- data aggregation - constant and comparable accounting principles	- requires the banks themselves to conduct stress tests using the predefined scenarios
Drawbacks and Advantages	- not tailor-made for each bank, but rather for a banking system as a homogenous entity	- more tailor-made for each bank
	- specific risks and interconnections may vanish on the aggregate level	- takes into account possible interdependencies across institutions
	- data aggregation as a source of non-accuracy	- data sets are richer, so the results more realistic
	- same methodology and assumptions	- the comparability of the results may be threaten by varying methodologies applied
	- burden on the supervisory authority	- costly for the individual banks, expert skill-intensive

The **bottom-up** approach requires the supervisory body to collect and use individual stress tests conducted by participating financial institutions and add up the obtained results in order to get the overall result of the aggregated (system-wide) stress test. In order to give reliable results of vulnerabilities of the whole system, the supervisory body has to ensure that individual banks and financial institutions use consistent stress test methodology. This methodology has to be applied across all institutions involved in the aggregate stress test.

As noted by Kalirai and Scheicher (2002) the bottom-up approach is easing the burden of the supervisory bodies, as it is using the stress tests already conducted. However, there are several serious drawbacks when relying on the bottom-up approach. Firstly, the bottom-up approach requires the supervisory body to state a common scenario that should be applied in individual institutions. To implement this scenario of the stress test across the financial institutions can be very costly and difficult. Direct involvement of individual banks in the system-wide stress testing exercise requires expert skills in the field of macroprudential analysis and model construction, which can be rather costly. Moreover, there exists the danger that financial institutions could interpret the central banks' interest in a particular scenario as containing some important information about the future development or likelihood of such a scenario to occur (CGFS, 2000).

Second, even when considering the alternative of asking all participants to use identical scenario for the stress test, the supervisory body has to ensure that the methodology to evaluate risks applied across the financial institutions does not differ significantly and thus does not result in non-comparable outcome.

Moreover, applying one common scenario and methodology across all financial institutions result in non-customized stress test. Different institutions have different portfolios and thus different risk exposure, e.g. one bank can focus on domestic market whereas another bank's highest risk exposure can be towards foreign currencies. More to the point, on the domestic market one bank can focus primarily on housing market (e.g. mortgage loans) and thus have different significant risk factors. Therefore, the "one-size fits all" scenario may not fit the needs of all individual banks.

The second approach – the **top-down** approach – requires the central bankers to aggregate the portfolio and balance sheet data from individual financial institutions and then conduct the stress test on the aggregated data. This approach impose higher burden on the supervisory body, as it can be resource-intensive and requires the central bankers to have more detailed knowledge on the disaggregated data of the individual banks (Blaschke *et al.*, 2001). On the other hand, supervisory bodies usually already do collect range of data from the individual financial institutions as a basis for their work. However, as mentioned by Kalirai and Scheicher (2002) the institutions included in the aggregate stress test must still follow the same reporting and accounting guidelines to ensure the comparability of the data.

Once the supervisory authority succeeds in collecting the detailed and disaggregated data on individual portfolios, the stress tests can be performed either on the balance sheet data of individual banks or on the consolidated portfolio representing the financial system. The former approach takes into account correlations between the portfolios as well as the linkages between the risks faced by the individual institutions. However, this approach requires access to detailed and disaggregated data on individual portfolio positions. The latter approach avoids problems of data availability and aggregation issues, but ignores on the other hand the possible contagion effects in the interbank system (Sorge, 2004). The top-down approach to stress testing brings often less accurate results, because the stress tests are usually carried out on aggregated system-wide data (Quagliariello, 2009). On the other hand, the top-down approach ensures usage of the same definitions and methodology.

Blaschke *et al.* (2001) believe that the bottom-up approach can provide the best informative picture about the vulnerabilities of the system as whole. This is because the individual institutions have the best knowledge about their own risk exposure and the strongest incentive to run an accurate stress test. However, the shared understanding is that since both approaches have its advantages and disadvantages, the best picture is obtained when combining both approaches. A cooperation of the macroprudential and microprudential approach when identifying the vulnerabilities in the system may also promote better communication between the supervisors and banks when implementing the micro- and macroprudential policy measures (Melecky and Podpiera, 2010).

2.2.3 Limitations and methodological issues

The following listing of limitations and methodological issues applies mainly to issues connected with stress testing on aggregate level.

a) Scope and choice of institutions

Most of the stress tests carried on the supervisory level are performed on aggregated basis of the individual institutional portfolios. When considering the stress testing of the country's financial system, the supervisory authority has to define the aggregated portfolio of the institutions. As pointed out by Quagliariello (2009) aggregating the portfolios of all financial institutions in the system does allow a comprehensive simulation of effects of the shocks, is however very computationally burdensome and in many cases nearly impossible. Therefore, for the perspective of financial stability of the country, the scope of the stress test can be restricted to a selected group of core institutions or major players that play a crucial role in the stability of the system and/or are most likely to be affected by the adverse event.

The selection of the group of intermediaries requires deeper knowledge about the structure of the financial system, since omitting key financial institutions or whole group of intermediaries may overlook potential vulnerabilities and contagion channels in the system. Main attention of the stress tests is typically focused on banks, since banks are usually the most significant institutions in the financial system of many countries. Moreover, as mentioned by Quagliariello (2009) banks - due to their role in payment systems - are a potential source of systemic and contagion risk. The selected group of institutions may differ from one country to another, as it depends on identified main risk exposures of the given system as well as on structure of the financial system. In countries where for example non-banking financial institutions play a significant role in the process of intermediation the scope of aggregated stress tests would have to be extended. Jones *et al.* (2004) emphasized that restricting the scope of the stress test only to the banking sector can lead to neglecting of complex institutional links in the financial system. In addition, Blaschke *et al.* (2001) pointed out that the role of foreign ownership should be taken into account when considering the scope of the aggregate stress test. Depending on the parent group, the banks with foreign ownership could absorb or transmit the shock in the domestic economy (Blaschke *et al.*, 2001).

b) Aggregation issues

Another methodological issue that is connected with the aggregate stress test is the process of aggregation. As mentioned previously, there are basically two approached how to conduct aggregate stress tests. The central bank can either collect raw data from the individual institutions and conduct the stress test on the collected data or compile the results of the stress test performed by the institutions themselves. Both approaches have its pros and cons as described in section 2.2.2 and summarized in Figure 3.

c) Data availability

One of the key assumptions especially when conducting aggregate stress tests is the availability and quality of the data. Similarly to other economic applications stress testing exercise heavily depends on the data available. Data information needs can vary significantly depending on many elements of the stress test exercise, such as the complexity of the scenario, different types of risks included in the stress test and potential interaction of risk variables (Cannata and Krüger, 2009). Stress testing can be therefore applied with varying degree of sophistication, depending on the data and information available.

Basic data availability, especially in countries that had undergone some structural changes and therefore the availability of long and stable time series data on the balance sheet exposures is limited, impose major constraint on the nature of the stress test exercise. Melecky and Podpiera (2010) conducted a survey of practices of stress testing in selected countries of Central and South Eastern Europe and pointed out that limited availability of data together with the inconsistencies among various data sources pose significant difficulty and major challenge in the stress testing development and reduce substantially the scope of the stress testing exercise.

Beside the basic needs with regard to the balance sheet data of the financial institutions, the stress test can be restricted by the difficulty of isolating specific exposures (for example institutions that are active in the derivative markets or large and complex institutions) and lack of risk data (duration and default measures). Jones *et al.* (2004) lists among the various constraints imposed also the confidentiality issue, i.e. the limitation imposed on the central banks when publishing the results of the stress test or sharing the sensitive information with the public.

2.3 Usage of stress testing – Why to stress test?

As mentioned previously, the observed results from the stress testing process serve generally speaking in determination of the stability and evaluating of the vulnerabilities of the examined system.

The wide range of uses of stress test can be again divided into two aspects depending on the examined system, i.e. whether the stress test is applied on the aggregate (macroeconomic) level to the whole system or as a risk management tool to the particular portfolio of the institution.

On the portfolio basis, the stress testing is usually used in the collaboration with VaR to capture the impact of an exceptional but plausible large loss event on the portfolio (see section 2.2.1). Stress test can - unlike VaR - simulate the performance of the portfolio during abnormal market periods connected to extreme price movements. More to the point, as pointed out in the survey conducted by CGFS (2005) some institutions are using stress tests to verify the distributions assumed in their VaR models.

In addition, stress test exercise can be used on the firm level for better understanding of the risk profile of the firm. A stress test can reveal exposures that are not significant on the individual business unit level, but can - in aggregate - have significant effect on the firm's business (CGFS, 2005). Hence stress test can serve as a tool in understanding the vulnerabilities of the firm and evaluating its tolerance towards risk. Besides the better understanding of its own risk profile, the individual institutions can use the stress testing techniques in order to assess the adequacy of their internal capital.

The stability of the whole financial system became the centre of attention of the various supervisory bodies as well as policymakers in recent years. The recent crisis has shown the vulnerability of the financial system doesn't have to stem only from endogenous factors but also as the consequence of adverse development of the macroeconomic and financial environment. Since any instability in the financial and macroeconomic environment can potentially has a substantial impact on the functioning of the financial system, which in turn could affect the real economy and therefore imply the second-round effects on the financial system, the supervisory bodies attempt to find a way how to understand the risks in the system, and hence reduce the likelihood and the impact of the potential adverse shock or crisis events (Trapanese, 2009). Hence, in contrast to stress test undertaken by individual banks or firms, the financial stability stress tests run by the central banks are generally more macroeconomic in nature and focus on the system-wide effects of the macroeconomic shocks.

When talking about purpose of stress test, Melecky and Podpiera (2010) distinguish between relative and absolute stress test based on the reliability of the underlying data and the interpretation of the results of the stress test. Absolute stress tests are understood as stress test capturing highly precise scenarios with all the relevant risks including their interplay and integration into the final outcome indicators. Since capturing all risks in the system and constructing highly precise and consistent models, that will eventually arrive on concrete numbers and absolute amounts is very burdensome, the relative purpose of the stress test focuses rather on relative interpretation of the results of the stress test exercise. Melecky and Podpiera (2010) define the relative stress test as a 'peer-group analysis when banks are stressed by what is considered a reasonably strong stress scenario and then bank-specific results compared to the average of their peer group'.[6]

When considering the system-wide stress test conducted by the supervisory bodies and usually published in their financial stability reports, the main aim can be summarized as test analysis of the resilience of the financial system towards different shocks caused by adverse macroeconomic and market conditions. According to Blaschke *et al.* (2001) stress test provide information on the source of the risks in a portfolio that can be relevant for decision makers – either policymakers or senior management level of the institution.

Macro stress tests provide forward-looking information on the impact of the possible extreme event on the resilience of the financial system. Hence, when results and outcomes

[6] Melecky and Podpiera (2010), pp. 3

from the stress testing exercise understood correctly, the assessment of the extreme but plausible shocks can be of great value: The difficulty of identifying the future crises and/or what might happen to the financial system (or possibly the individual firms) given the certain risks to occur, can be forecasted or mitigated to some extent.

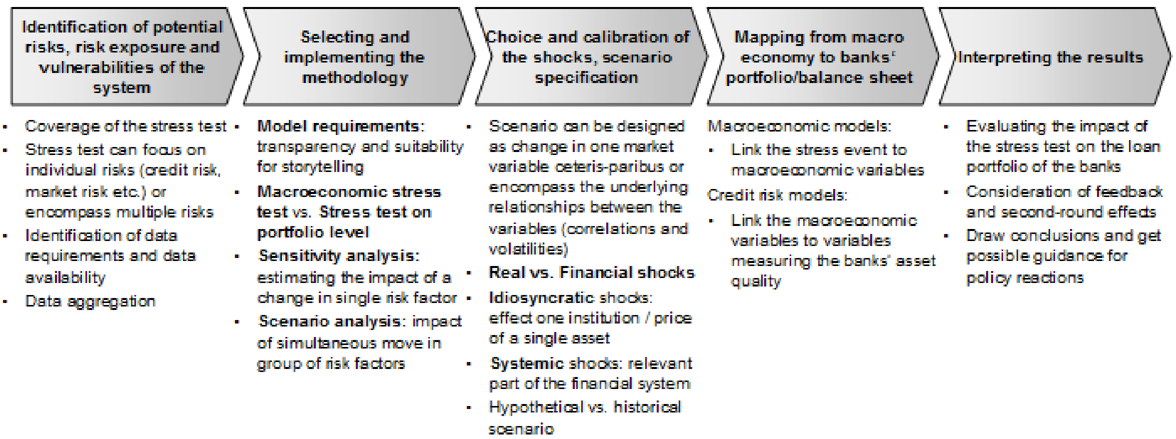
Stress tests can also reveal potential hidden correlations across portfolios, for example the correlation between corporate sector and households, when both sectors could be hit by the same macroeconomic shock and respond in the same direction (Bunn, Cunningham and Drehmann, 2005).

Moreover, as mentioned in Baudino (2009) stress tests can identify information gaps between the private banks and the supervisory bodies. Stress tests are usually used as a good platform to encourage communication and cooperation between central banks and private banks. Publishing the results of macro stress tests run by the central banks promote cooperation among the institutions and central banks, both nationally and internationally.

2.4 Stress testing process

The process of stress testing the whole financial system requires development of comprehensive tool kit, starting from forecasting techniques, proper identification of the adverse economic shock as well as the correct calibration of the shock, interpreting the impact of the shock on macroeconomic environment and the whole system and drawing some management and policy implication and advices.

Figure 4: Main components of macroeconomic stress testing



Source: author based on Blaschke *et al.* (2001), Bunn et al. (2005), Quagliariello (2009) and Foglia (2009)

Notes: for a typical stress test process schema see also Čihák (2007), Foglia (2009) and Jones *et al.* (2004)

2.4.1 Identification of potential risk factor and vulnerabilities of the system

The process in the stress test exercise begins primarily with determination of the stress test coverage and selection of intermediaries, i.e. the main focus of the stress test. Considering the whole financial system of the country would allow a comprehensive simulation of the effects of the adverse shocks, however, this approach would be extremely computationally burdensome (Quagliariello, 2009). Therefore, the majority of the macro stress tests focus on the significant and major players in the country's financial system. As a rule of thumb, most stress tests applied to the "whole" financial system are in reality performed only on a subset of systemically important institutions.[7] Typically, the macro stress tests are mainly run on the banking sector as a subset of the financial system, since banks are the most significant financial intermediaries in many countries (Quagliariello, 2009). When restricting the scope of the macro stress test on banking sector only, the outcome of the stress test exercise may, however, ignore the complex institutional links among the different categories of the financial intermediaries and therefore may not provide exhaustive assessment of the resilience of the system.

The choice of the scope of the macro stress test exercise heavily depends partly on the nature of the risks that need to be analysed and partly on the data available. Selection of the scope of the stress test often involves a trade-off between accuracy of the exercise and computational and reporting burden.

Next step in the stress test exercise is identification of major risks and vulnerabilities of the system. Again, since stress tests do represent the reality only in a simplified fashion and can't therefore cover every possible risk factor for the portfolio or system, the researcher usually narrows down the focus on the main risk factors and weakest points in the financial system, he is interested in understanding. Similarly to the selection of intermediaries, the step of indentifying the main risk factors and exposures allows to tailor the stress test exercise to the needs and conditions of the country. Focusing on the country-specific significant exposures makes the process of stress test more effective and prevents waste of time and resources (Jones *et al.*, 2004).

[7] Čihák (2007) pointed out that only minority of the FSAP macro stress tests are conducted on the whole financial sector of the given country. On the contrary, the majority of the macro stress tests run in the IMF FSAP focused on subset of large banks that covered generally 70 – 80 percent of the total assets in the banking system.

Identification of the risks that are most likely representing the danger for the system is an analytical process involving both qualitative and quantitative components (Jones *et al.*, 2004). Knowing the characteristics of the examined system, the structure of the financial intermediaries, share the individual categories of the intermediaries represent in the financial system, the main business carried out in the system together with the broader macroeconomic conditions and development represents only the basics when considering the identification of the potential vulnerabilities of the system.

2.4.1.1 Financial soundness indicators

When conducting the macro stress test, the impact of the shock as well as the overall resilience of the system can be examined using wide range of numerical indicators. Jones *et al.* (2004) summarized various types of numerical indicators that can be used in order to isolate the potential weaknesses of the system. Ranging from macro-level indicators, that provide the overall context for the performance of the system and allow the comparison of the development, with respect to its own historical experience as well as the comparison of the development towards other countries and peer groups, to structural indicators, that can indicate significant risk exposures in the financial system.[8]

The so-called Financial Soundness Indicators (FSIs) were developed in order to assist and provide guideline on the assessment of the financial soundness of the system and quantify the systemic importance of various risk exposures and vulnerabilities.[9] The construction of the set of FSIs aimed to provide participating counties on the guide, how to access the sources of vulnerabilities in its own financial system. The macroprudential analysis of the FSIs aims to provide a basis for actions and policies that would prevent financial crisis from occurring.

The FSIs belong to micro-level indicators, since these indicators are typically derived from financial statements of the individual institutions. When drawing up the list of the indicators, the main focus lied on the core markets and institutions, the FSIs are usually of analytical importance for many countries and relevant in many circumstances, so they can be applied widely. The core set of the FSIs contains many indicators covering deposit

[8] For detailed description and explanation of the macro and structural indicators see Jones *et al.* (2004) pp. 7-12.

[9] The FSIs were presented for the first time in June 2001 as part of the Financial Sector Assessment Program (FSAP), joint initiative of the World Bank and IMF. Later, the core and encouraged set of FSIs had undergone some changes and improvements as a response to the changing financial environment.

takers and comprises measures of capital adequacy, asset quality, liquidity, earnings and profitability and sensitivity to market risk. Since many of the indicators are basically ratios derived from the aggregated financial statements, the analysis provides valuable insight into the stability of the system. Needless to say, the indicators itself do not provide a fully comprehensive assessment of the system stability.

2.4.2 Shock calibration and scenario specification

Next step, once the major risk triggers for the system are identified, the scope and main focus of the stress tests specified, is to put together a coherent stress test scenario. Designing and calibrating a scenario typically involves number of elements:

- Choice of the type of risks to be analyzed, focus on single or multiple risk factors
- Parameters to shock (prices, volatilities, correlations)
- The magnitude of the shock
- Time horizon

Shock calibration is often based partly on the expert judgment and partly on the discretionary assessment of the analysts (Quagliariello, 2009). Since the stress test exercise aims to examine the impact of the adverse event that is beyond the normal range of experience the implementation of the scenario is often an iterative process (Quagliariello, 2009; Čihák, 2007).

The stress test exercise can have a form of a simple **sensitivity test** (aka univariate stress test), where the change in portfolio value for a single risk factor is examined, or it can have a form of scenario analysis, where the impact of simultaneous moves in group of risks is considered. Sensitivity stress tests are usually easier to implement and the results are straightforward to interpret.[10] However, sensitivity scenarios ignore multiple risk factors and the correlations between the risk factors. Moreover, they do not allow the feedback effects to be taken into account in the simulation. Hence, they can provide first assessment

[10] Examples of the simple sensitivity stress test are following:

Interest rate risk: Parallel shifts and steepening or flattening of interest rate curves; increase or decrease in interest rate volatilities
Credit risk: parallel shifts of credit spreads curves, acceleration in the volume of NPLs
FX rates risk: Appreciation or depreciation of the underlying currency; increase or decrease in FX volatilities
Equities: Increase or decrease in spot prices and equity volatilities
Commodity risk: Increase or decrease in spot prices of commodities (oil price etc.)

of the portfolio's sensitivity to given risk factor and serve as a rough approximation of the loss (BCBS, 2009).

The more sophisticated approach – the **scenario analysis** – enhances the predictive power of the stress test exercise, since it encompass multiple risk factors and overcomes therefore the shortcomings of the simple ad hoc sensitivity analysis.[11] On the contrary to the sensitivity analysis, where the time horizon is typically shorter, often instantaneous and the source of the shock is not defined, source of the shock in the latter approach is usually well defined and the time frame is longer (CGFS, 2005).

The scenario is typically constructed either as historical scenario (based on the historical data) or hypothetically. The **historical scenario** is constructed based on the observed past development, typically the change in the risks factors experienced in the various historical episodes[12] are applied to the portfolio. The advantage of this approach is that this is tangible and intuitive, since the stress event was already observed in the past. Moreover, as one of the roles of stress test is also facilitation of the communication (especially true when applied within an organization or company), the advantage of the historical scenario is its transparency and relatively easiness to understand (CGFS, 2000; Quagliariello, 2009). On the other hand, historical scenarios are rather backward-looking, as they are derived from past experience, and therefore can ignore the change in risk-taking appetite. More to the point, historical scenarios fail to capture new products or significant changes in the behaviour of the market and therefore may no longer be relevant for the specific system (BCBS, 2009; Blaschke *et al.*, 2001; CGFS, 2000). Classical example of the historical stress test scenario is for example the Gulf War scenario– used to stress test the commodity risk related exposures, LTCM or 9/11.[13]

Hypothetical scenario represents more realistic option, especially in the cases where the structure of the financial system changed significantly in the past (for example, periods of privatization, deregulation, liberalization etc.) (Jones *et al.*, 2004; Quagliariello, 2009).

[11] Main reason why to use scenarios rather than single risk factor shock is that typically change in several risk factors occurs or the risk factors are interrelated. Hence, the financial institution is affected by the direct impact of the initial shock but also by indirect impacts by other factors caused as a result of the initial shock or by the contagion effects (Čihák, 2007).

[12]The analysts identify the days that imposed some stress on the system and use the observed changes in the risk factors (CGFS, 2000).

[13] See CGFS (2000) or Quagliariello (2009), pp.30

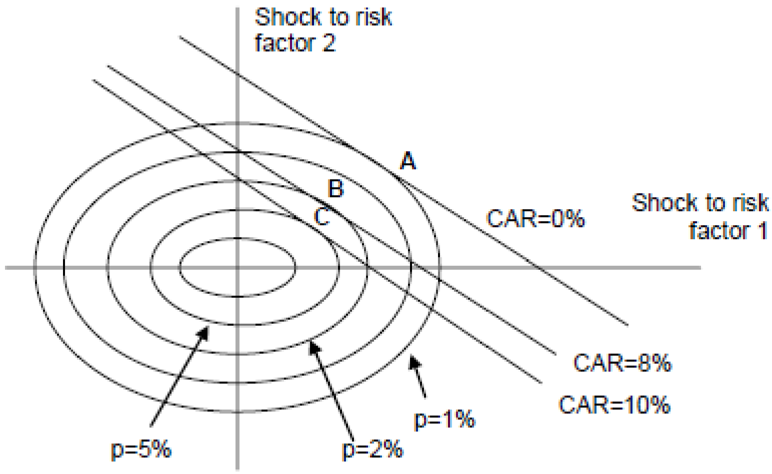
Hypothetical scenario is generally based on expert judgment and involves some sort of macroeconomic model.[14] The use of the historical experience helps the expert to set the correct magnitude of the shock. Hypothetical scenarios[15] are more flexible and overcome the major drawback of the historical scenario, namely, they are forward-looking. The disadvantage of hypothetical scenario lies within its very nature - if the model is not specified properly, the correlations between risk factors can be incorrect and therefore the scenario may not fit the commonly observed movements on the market. Second shortcoming is the difficulty to attach probability to hypothetical scenario (Jones *et al.*, 2004; Blaschke *et al.*, 2001).

Besides the two widely used approaches how to build the adverse scenario, some stress tests can apply the so-called “**worst case approach**” and the “**threshold approach**” when constructing the scenario.

[14] Melecky and Podpiera (2010) distinguish in their paper on macro stress testing between approach based on judgment decision and model-consistent approach when constructing the scenario. The first approach relies on the experts’ judgment and decision on the relevant economic variables that are used in the stress testing exercise. The latter approach builds the scenario based on a macroeconomic model that is in line with the economic theory, and therefore interlinks the macroeconomic variables among each other. Both approaches have its pros and cons, however, according to Melecky and Podpiera (2010) the approach based on the experts’ judgment proved to be too optimistic.

[15] Hypothetical scenarios encompass multiple risk factors and can simulate some past crisis event as well, for example “financial crisis” scenario could potentially look as following: stock markets fall related to an increase in equity volatilities, decrease in interest rates and dramatic widening of credit spreads.

Figure 5: Worst case and threshold approach



Source: this figure is adopted from Čihák (2007), pp. 48

Notes: The definitions and the main idea are taken from Čihák (2007), pp. 46 – 48. The two axes display the two risk factors that are interrelated between each other. The ellipse represents the set of combinations of the two risk factors with a certain probability of occurrence. The correlation between the risk factors is depicted with the shape of the ellipse and the size of the ellipse represents the plausibility (p). The impact of the shocks is measured by the change in capital adequacy ratio (CAR), represented by the diagonal lines in the picture.

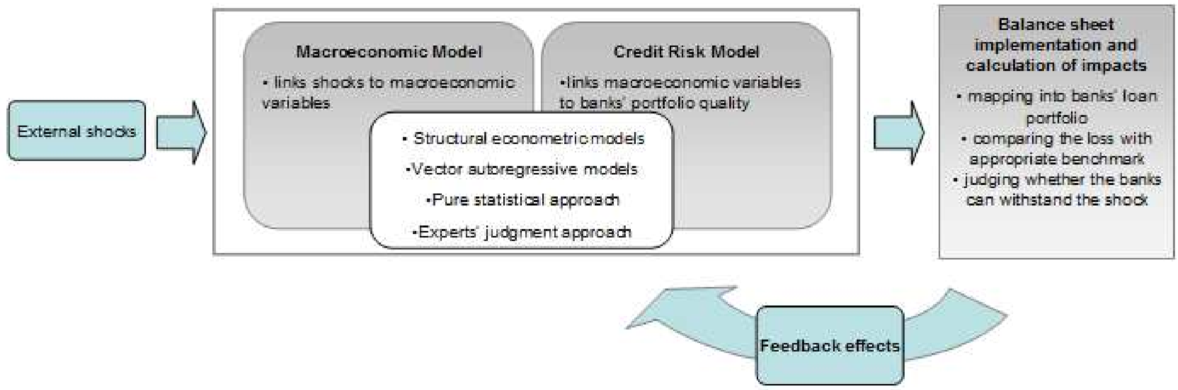
Figure 5 illustrates the worst case and threshold approach in building stress test scenario for two risk factors. The **worst case scenario** can be defined as a scenario, which given the certain level of plausibility has the worst impact on the system. In other words, given the level of *p*, we are searching for a point, where a diagonal line represents a tangent to the particular ellipse. The **threshold approach** represents the same problem, but starts with selecting the threshold of the impact of the shocks, i.e. the diagonal line (Čihák, 2007). Hence, the threshold approach can be defined as the largest possible shock that would leave the system or examined portfolio above a certain threshold (measured by capital adequacy or profit) (Quagliariello, 2009).

Typically, the decision how to construct the stress test scenario depends on the complexity of the system and the availability of a suitable model depending again on the quality and availability of the underlying data. Generally speaking, the choice and calibration of the scenario usually faces a trade-off between computational burden involved and the realistic prediction of the impact of a stress event.

2.4.3 Implementing the scenario and mapping the macro scenario to the balance sheets

Once the adverse scenario for the stress test is defined, the next step in the stress testing process is implementation of the scenario. Since the implementation of the adverse scenario requires the central bankers to know the expected movements in key macroeconomic variables, macroeconomic models are usually applied in order to understand how the system behaves when assuming the adverse shock. The role of the macroeconomic model is to link the stress event to the key macroeconomic variables. Moreover, the linkages and relationships between the macroeconomic variables are very important for the stress testing purposes. As mentioned in Quagliariello (2009), these models are typically constructed by central banks in order to forecast the development of the macroeconomic variables.

Figure 6: Macro stress testing framework



Once the macroeconomic model has been applied, the key macroeconomic variables under the stress event estimated, the contagion effects and the transmitting mechanism has to be captured in order to assess the impact of the adverse shock and calculate the expected loss. However, macroeconomic models typically do not incorporate all the necessary features (they do not include a measure of credit risk), therefore one single model is not able to provide the whole picture. Hence, often credit risk models have to be developed in order to link a measure of credit risk to the macroeconomic model variables. These models usually take a form of a reduced-form econometric equation model (Foglia, 2009; Quagliariello, 2009).

Foglia (2009) divided various types of models that are used to map the shock to macroeconomic variables and models to map the credit risk measure to macroeconomic variables into structural econometric models, vector autoregressive models and pure statistical approach. In addition, Melecky and Podpiera (2010) added the judgment based approach (mainly when building the coherent scenario). They pointed out, the judgment based approach is applied in cases when robust statistical or econometric models are not available or the underlying data are not sufficient to form a basis for a sophisticated model. This approach however faces serious shortcomings when the structural economic consistency and consistency over time of the stress test is considered.

Structural models are applied usually in central banks, where robust models for forecasting and policy analysis are already available. These models typically take the initial shock as exogenous and return the values of macroeconomic variables projected over time horizon of the stress test event. Application of the structural model ensures consistency across the predicted variables and allows incorporation of endogenous policy reaction to the initial shock. However, structural models are usually not capable to capture the non-linear relationships between the variables (non-linear relationships are often observed especially in times of stress or for example when realizing regime switch). Moreover, the structural models face the difficulty of determining the likelihood of the adverse stress scenario (Foglia, 2009; Quagliariello, 2009; Melecky and Podpiera, 2010).

In cases, when structural model is not available, vector autoregressive (VAR) or vector error correction models (VECM) are employed. These models are favoured because of their flexibility and relatively easy way of producing consistent set of predicted variables, however, often criticized for their inability of “storytelling” and therefore unsuitability in cases where policy evaluation or communication is the main objective (Drehmann, 2008; Foglia, 2009).

The choice of the suitable approach depends again largely on the available data, on the main risk examined and on the objective of the stress test. Drehmann (2008) showed how different objectives lead to different and often conflicting priorities when constructing the model.

2.4.4 Interpreting results and second-round effects

The final step in the stress testing process is interpreting of the obtained results, i.e. calculation of the bank losses under the stress event. Typically, bank-by-bank impact of the stress event is expressed in terms of some variable or indicator of financial soundness (such as capital adequacy or solvency ratio) in order to assess the ability of the bank (and the whole system) to withstand the shock assumed.

Several issues can arise when interpreting the results of the stress test. First of all, the choice of variable to measure the ability of the institutions to withstand the stress event depends usually on the model used. Typically, the impact of the stress event on the institutions is compared to some baseline scenario, in which the banks (institutions) remain profitable and solvent. Depending on the model, the researchers usually assess the impact of the shock either by forecasting the expected increase in the loan loss provisions or by computing the expected default rates. The computed loss is then compared with some appropriate benchmark and the ability to withstand the shock is determined.

The buffer that is employed by the institutions to face the stress event is usually capital, however as mentioned for example in Foglia (2009), banks would typically exhaust profit first before reducing the capital or other balance sheet positions. More to the point, Foglia (2009) pointed out that expressing the results of the stress test exercise in terms of capital only can lead to overestimating the actual impact in those cases, in which the institutions would otherwise remain profitable in the baseline scenario. Central banks typically do express the outcomes of the stress test in terms of capital adequacy and state the need for the recapitalization, since the effect of the stress test exercise on the capital adequacy ratio is of particular interest of supervisory bodies.

Second drawback discussed in connection with expressing the outcome of the stress test is that the number generated by the stress test model is usually not an accurate point estimate of the expected loss, but rather an assessment of the possible risk (Drehmann, 2008). To overcome the problem, some papers attempt to derive an entire profit and loss distribution for the loan portfolio of the system and hence allow computation of the probability of loan losses with various sizes. The entire loss distribution makes it possible to calculate the expected loss of the entire loan portfolio and therefore the capital buffer the banks are required to hold against the loss that is above the obtained expected loss (Foglia, 2009).

The last issue mentioned for example in Quagliariello (2009), Foglia (2009) and Čihák (2007) is that the central banks have to calculate the effect of the stress test scenario on the individual banks and not only for the aggregated level. The aggregate level approach to the stress test may hide important information about the distribution of potential risk exposures among the various institutions. As mentioned in Drehmann (2008) the level of aggregate liquidity in the system is often not the issue even in times of stress, however, the distribution of liquidity plays the crucial role. The institutions may have different preferences and take different levels of risk with regard to the risk factor. Those with the highest risk-appetite are likely to fail under the stress event – banks usually became illiquid before they are insolvent – and hence would no longer be able to meet the capital requirements. Nevertheless, the average capital adequacy ratio for the whole system may still remain above the minimal capital requirement level. In fact, the actual distribution in the system is particularly essential when assessing the threat of the contagion effects in the system, since failure of major intermediary may induce through for example counter party credit risk serious threats to other market participants. Needless to say, that this analysis requires the micro-level data on the individual institutions (Foglia, 2009; Drehmann, 2008).

3 Development in the banking sector

Following section of the thesis describes the development in the Czech banking sector. The Czech Republic is an example of a bank-oriented financial system and hence, traditionally, the banking sector has been the most important channel of financial intermediation.[16] The following analysis of the current state of health of the financial sector (in this case the banking sector as the most important part of the financial sector in the Czech Republic) is the first step in assessing the fragility of the financial system.

The Czech banking sector had undergone some turbulent years after the change to market economy in 1989. The first decade was characteristic by the effort to quickly overcome the burden inherited from the central planning system. The socialist one-bank-system was replaced by four large state-owned banks and the benevolent licensing policy and regulation encouraged period of quick expansion of the banking sector. Because of the absence of sufficient legal framework and institutional supervision, as well as managerial know-how, the banking sector quickly started to face serious problems. As a result of the bad situation in small Czech banks and in order to prevent domino-effect in bank failures and ensure the creditworthiness of the system, the Czech National Bank adopted various stabilization measures and programs.[17]

The overall macroeconomic conditions in the late 1990s together with more cautious lending policy adopted by the banks manifested themselves in the period of decline in bank lending. Bárta and Singer (2006) show the decline in loans granted by the banks during the period until 2002. Only starting from 2003, after the privatization of the four large state-owned banks, the lending activity recovered.

The following section of this chapter will focus mainly on the period from 2002 to 2010, because this time period is relevant to the empirical part of the thesis. Moreover, data indicating loan portfolio quality (such as the non-performing loans) are publicly available only after the year 2002. The development of the portfolio quality of the Czech banking

[16] According to data published by the Czech Statistical Office, the financial sector of the Czech Republic had total assets amounting to CZK 6257 billion, which was approximately 170% of GDP at the end of 2009. Deposit money bank assets expressed as a share of GDP comprised to 1.15, non-banking money institutions amount to 0.26, insurance companies 0.12, financial leasing companies 0.08. The share of assets to GDP of pension funds and investment funds was 0.06 and 0.04, respectively.

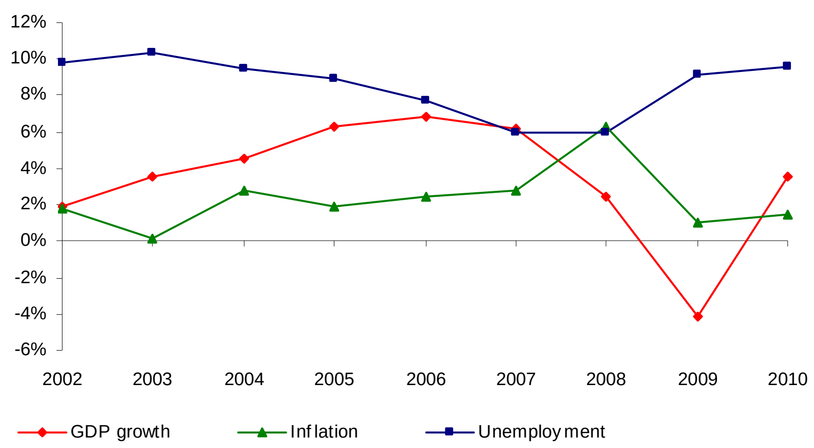
[17] For detailed description of the early development of the Czech banking sector as well as the process of consolidation and stabilization see for example Bárta and Singer (2006), Tůma (2002) and Dědek (2001).

sector before the year 2002 was affected by the effort to establish healthy banking sector. Balance sheets of the large banks were cleaned up from the bad loans accumulated during the transitional period.[18] The Czech banking sector has been stable for the selected studied period and dominated mainly by foreign strategic owners.

3.1 Macroeconomic conditions

Development of the credit market and hence the quality of the loan portfolio is assumed to be connected to the overall development of macroeconomic conditions of the country and to the economic activity. This section describes the main indicators of the economic activity of the Czech Republic over the period of 2002 to 2010.

Figure 7: Development of GDP, inflation and unemployment



Source: ČSÚ, ČNB

Notes: Growth rate in GDP calculated from index number (GDP Volume, 2005=100), growth rate of GDP for 2010-year end is an estimate based on the actual real data for third quarter of 2010. Inflation rate is calculated as an increase in average annual CPI indicating percentage change in last 12-month average over preceding 12-month average, according to the definition of ČSÚ.

From macroeconomic point of view, the period from 2002 – 2006 was characterized by positive performance in the Czech Republic. Annual GDP growth was constantly increasing over this period starting from 1.9% in 2002 and reached its peak in 2006 with 6.8%. In 2006, economic growth in the Czech Republic was one of the fastest among the EU member states. In 2007, the favorable economic development continued despite the erupted financial crisis, the annual growth rate of GDP remained high at 6.1%. The labour

[18] Major rounds of clean-ups appeared in the beginning of 1990s (large banks were cleaned from bad loans in the first step) continuing in the second half with the shift to smaller banks.

market situation was good over the period of 2002 to 2007. The registered unemployment rate was gradually decreasing over this period from 9.8% in 2002 till 7.7% in 2006. Also in 2007, labour market situation improved and the economic growth in the Czech Republic was accompanied by new job creation and decline in unemployment rate, averaging at 6.0%. Inflation rate was fluctuating in the period from 2002 till 2006 around 2% on average. In 2007, inflation rate gradually increased compared to previous period, but still remained low at 2.8%.

The figure clearly reveals the impact of the economic crisis that affected the economic development in the whole Europe and in the Czech Republic in 2008. As it is shown later in the chapter, the adverse economic trends in economic activity had also an impact on the loan quality portfolio, since it affected the financial performance that in turn resulted in raising payment difficulties by both, businesses and individuals. Annual growth of GDP declined in 2008 by 3.7 percentage points compared to the previous year to 2.5% y-o-y growth. Also inflation rate continued to grow in 2008, the average inflation rate grew by 3.5 percentage points in 2008 compared to previous year and reached the level of 6.3%. Labour market situation reflected the economic crisis and the slowing of the economic activity and growth in 2008. The average registered unemployment rate increased by 0.4 percentage points compared to 2007 and was close to 6%.

According to the IMF (2010), the world economy proceeds to recover from the financial crisis with varying speed. The highest economic growth was achieved in countries of emerging Asia[19], especially in China and India with GDP growth around 6% and 9%, respectively. Among the developed economies, the economy of the United States with GDP growth rate at -2.4% in 2009 is recovering more successfully than Europe or Japan with GDP decrease by 4% and 5.2%, respectively.

In Europe, the recovery process was expected to be rather gradual and uneven among the individual countries especially among the members of the Euro area. A large part of the economies in the European Union experienced negative economic growth in 2009; also the Czech Republic was affected by the adverse macroeconomic situation. GDP decreased by 4.1% in 2009, also the labour market development indicated the economic recession that started in 2008. Labour market reflected the economic downturn with usual lag, the

[19] Emerging Asia comprises China, India, Korea, Taiwan Province of China, Hong Kong SAR and Singapore.

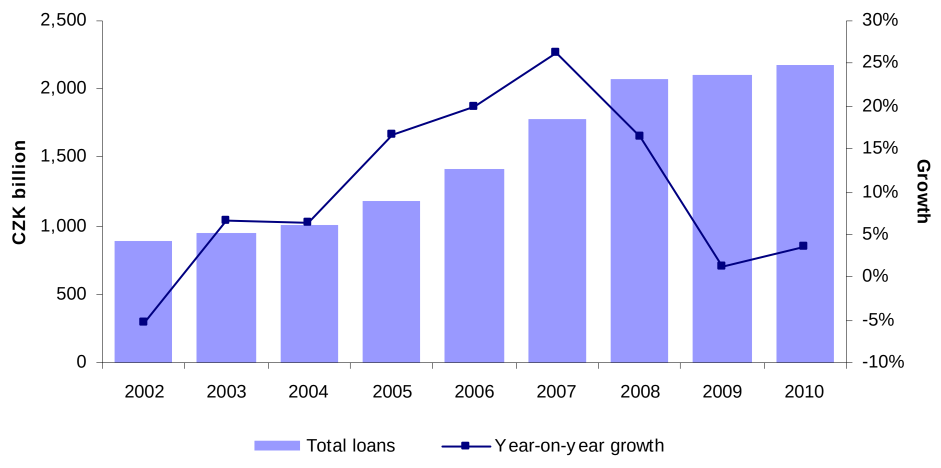
registered unemployment rate increased to 9.2%, up by 3.2 percentage points compared to previous year.

As a small open economy in the heart of Europe, economic growth is strongly influenced by demand for Czech exports and flows of foreign direct investment. The volume of the foreign trade was constantly increasing over the period of 2002 to 2007.[20] In 2008, the volume of export stagnated and in 2009 the volume decreased by 14% compared to previous year. Export activity is traditionally related to the export and investment activities with the member states of the EU[21], especially foreign trade with Germany, which created more than 30% of the total export in the Czech Republic in 2009.

3.2 Development of credit market

3.2.1 The loan portfolio

Figure 8: Development of total loans



Source: CNB

The volume of total loans granted by the banks towards residents and nonresidents rose significantly between the years 2002 and 2007, with average annual growth rate of almost 15%. Moreover, the growth of the total loans was very significant in the period from 2005 to 2007, when the y-o-y growth reached its peak with approximately 26% increase. During the period of rapid growth volume of total loans increase by approx. CZK 892 billion, which is, in other words, twice the amount that was granted by the banks in 2002.

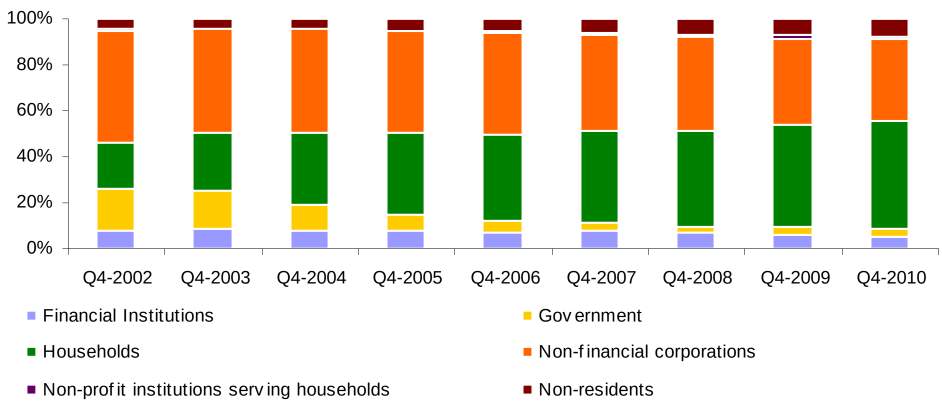
[20] See the graph in the Appendix

[21] In 2009, the volume of export into EU27 countries amounted to almost 85% of the total exported volume.

A **trend change** is apparent in the period from 2007 to 2009. During this period, the growth of volume of total loans started to decline rapidly. The y-o-y growth of total loans was 16.4% and only 1.3% in year 2008 and 2009, respectively. Particularly, the decline in growth in 2009 shows the rapid change in the lending trend by the domestic banks.

The results of the first three quarters of the year 2010 confirm the decreasing trend in lending activity. Percentage change to the previous respective quarters didn't exceed 2% in the first three quarters in 2010, however, the results show slightly increasing tendency in the development of lending activities. By the end of the year 2010, the volume of total loans increased by CZK 72.7 billion, this corresponds to 3.5% growth y-o-y.

Figure 9: Sectoral breakdown of the total loans



Source: CNB

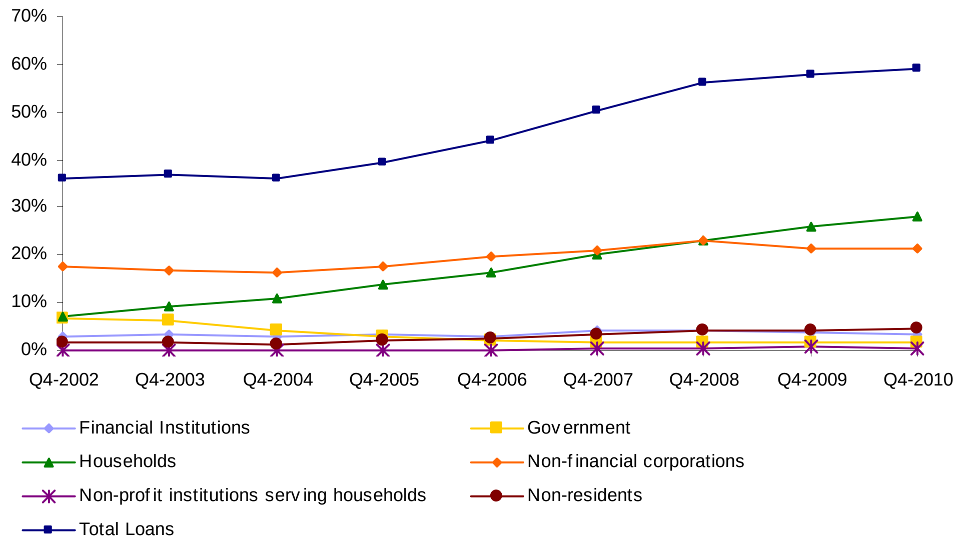
Figure 9 shows the **sectoral breakdown** of the lending in the Czech banking sector. The sectoral distribution of total loans to residents and nonresidents indicates the exposure concentration towards particular sectors. Whereas in the beginning of the observed period the majority of the total lending consisted mainly of loans to **non-financial corporations** and general government followed by lending to **households** (both individuals and trades), at the end of 2010 the majority of loans goes mainly to households and non-financial corporation. However, the portion of lending towards non-financial corporations is rather declining over the last three years.

The volume of loans granted to the general government decreased rapidly during the whole period by CZK 102.8 billion. On the contrary, the dynamic growth in lending to households is apparent in the whole period. From 2002 to 2010, the loans to households increased by almost 21 percentages points or alternatively by CZK 849.5 billion and loans to non-financial corporations rose in absolute terms by CZK 345.8 billion. As of December 2010, the share of loans towards households in total loans reached 47%, which was the highest in the portfolio. The share of non-financial corporations to total loans amounted to almost 36% in 2010, however, over the whole period the share recorded decrease by 12.8 percentage points.

From the credit risk exposure point of view, lending towards households is of particular interest, since households are usually affected by a crisis with some time lag (CNB, 2010). Moreover, worsening situation on the labour market may result in repayment difficulties realized by the households.

Figure 9 reveals the fact that domestic banks focus mainly on the **domestic market**. The fact is reflected by two elements: in the relatively low share of transactions with non-residents and low share of activities in foreign currency. Receivables to non-residents rose only moderately by 3 percentage points over the period from 2002 to 2010, and amounted to 7.7% of total loans at the end of 2010. The proportion of foreign currency activities decreased from 16% in 2002 to 13% of all transactions at the end of 2010. The largest part of the foreign currency activities are contracted in Euro. Since the beginning of 2002 the euro transactions reached almost 70% of foreign currency transactions and continued growing. As of December 2010, the ratio was 85% which is approximately 11% of total lending activity of the domestic banks.

Figure 10: Loans as a share of GDP by sectors



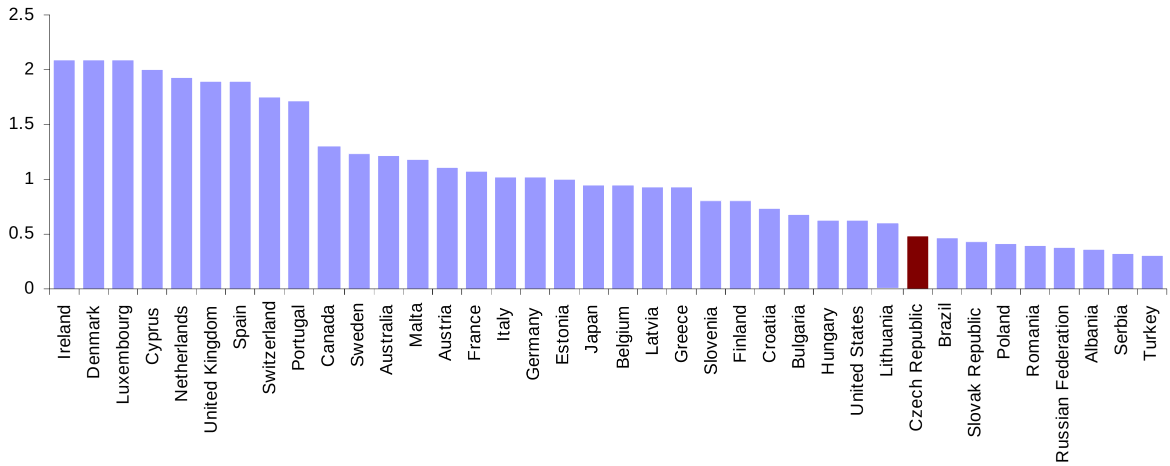
Source: CNB

Figure 10 shows the constituent sectors lending activity as a share of gross domestic product. The loan to GDP ratio is a general indicator of the **financial leverage** of the economy. The idea is straightforward: Low loan to GDP ratio can indicate the economy is not realizing its full potential. On the contrary, high loan to GDP ratio suggests the economy is increasingly over-borrowed. Loan to GDP ratio indicates the country's economic ability to sustain the debt. When private sector has borrowed excessively in relation to the economic prosperity, loan to GDP ratio is high. When the leverage becomes excessive the risk of widespread defaults increases. Even though the idea behind loan to GDP ratio as a financial leverage indicator is quite simple, the level of the leverage depends on many country-specific factors, mainly on the stage of development of the financial market. Generally, high-income countries tend to have higher loan to GDP ratio.

During the period from 2004 to 2007 not only the volume of total loans increased, but also the share of loans to GDP. The total loan to GDP ratio increased in the period of dynamic growth by 20.4 percentage points. The growth reached its peak in 2008 when the leverage amounted to 56.3%. As of December 2010, the ratio equals to almost 59.3%.

As mentioned previously, the trend in loans to non-financial corporations and loans to household was different to the other sectors. The share of loans to non-financial corporations developed over the period 2002 – 2008 with stable, slightly increasing trend. In the last two years, the ratio of loans to non-financial corporations to GDP decreased by approx. 1 percentage point. The dynamic growth in lending to households manifested itself in the ratio of provided credit to GDP. Whereas the ratio of non-financial corporations loans to GDP rose by 3.6 percentage point, the households ratio increased by 20.8 percentage points over the period from 2002 to 2010.

Figure 11: Credit to GDP ratio in selected countries[22] as of 2008



Source: IMF, World Bank

Despite the significant growth in 2008, credit to GDP ratio in the Czech Republic belonged to the lowest in the European Union. The comparison among high income countries reveals that the level of indebtedness of the Czech economy is still low. It is worth mentioning that the low level of initial indebtedness could be one of the reasons for the dynamic growth in lending activity in recent years.

3.2.2 Loans by type

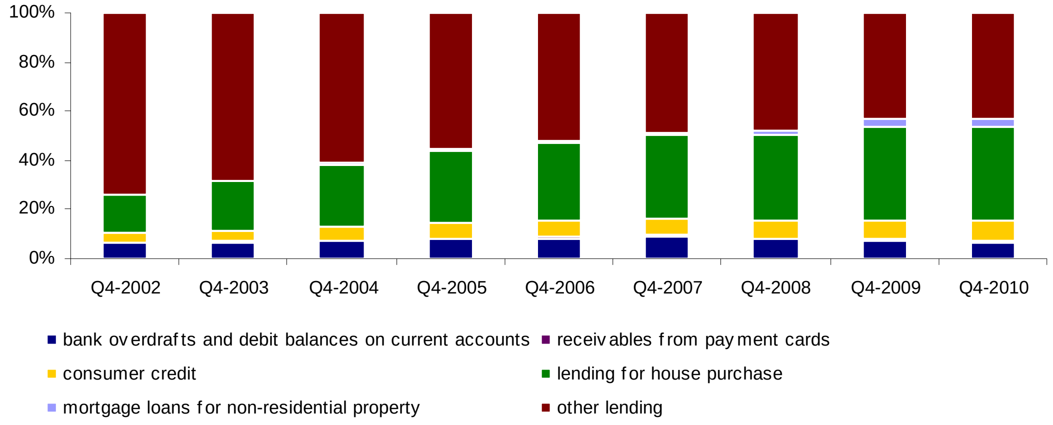
As clearly visible from the previous section, lending to households was the most significant and dynamic element of growth in the lending of domestic banks. Traditionally, private individuals' debt with the domestic banks was the main part of loans granted to households. Volume of loans provided to individuals accounted to 93.45% of total households' loans in 2010.[23] Since the beginning of the observed period, the loans to

[22] The sample consists of 27 high income countries, 10 upper middle income countries and 1 lower middle income country. The sample consists of all 27 EU member states. The World Bank classification for country income groups is used.

[23] Since 2000 the share of loans provided to individuals exceeded 70% of the loans granted to households and continued growing, although the growth was gradually slowing down. In 2010 the share of household loans provided to individuals dropped by 2 percentage points in comparison to year end 2009.

individuals increased more than six times and at the end of 2010 totaled to CZK 960.8 billion.

Figure 12: Loans by type



Source: CNB

Figure 12 shows the different loan types in the Czech banking sector provided to resident and non-residents. The figure clearly reveals that the structure of the domestic banking sector has been affected by the trend of lending for housing purposes in the last years. Again, the loans for house purchases are increasing every year, although the growth is slowing down. Since 2002 loans for house purchases rose by 22.3 percentage points and reached CZK 796 billion at the end of 2009.[24] As of December 2010, the loans for house purchases accounted for 38.25% of total loans. Consumer credit rose by 4 percentage point over the whole period and at the end of 2010 accounted to 7.5% of the total portfolio. Other lending[25] consists of several types of loans, out of which the most significant part are investment loans.

3.2.3 Portfolio quality

The quality of the portfolio is closely connected to the credit risk undertaken by the banks. Credit risk has always been the most significant risk in the domestic banks; moreover, the

[24] Lending for household purchases includes mortgage loans for residential properties as well as business properties (incl. rental), standard building society loans, building society bridging loans and consumer credit for real estate.

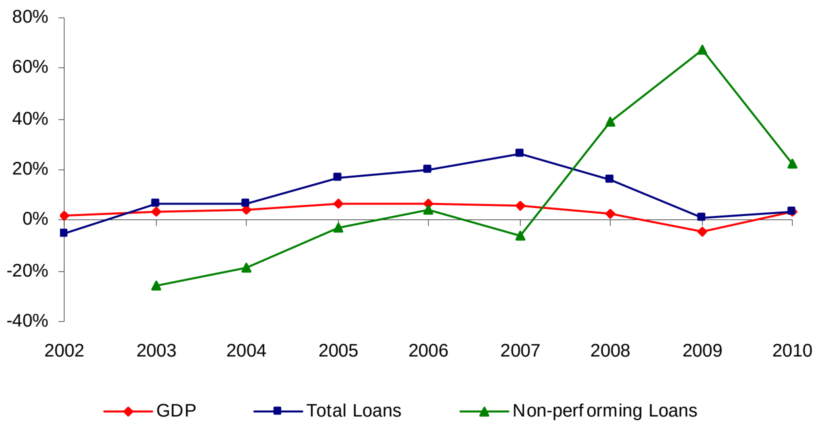
[25] Other lending includes following: investment, current assets, seasonal costs, export, import, temporary shortage of funds, other lending (financial and specific purpose), trade receivables, purchase of securities, small-scale and large-scale privatisation loans, subordinated loans and deposits, repo transactions and loans to unlicensed banks

dynamic growth in lending activities over the last 6 years indicates that its importance is still growing.

As mentioned previously, the balance sheet of the domestic banks had undergone major clean up operations in the past. The process of removing bad loans from the domestic banks was fully completed only in 2003. Starting from 2004, the volume of defaulted loans started to grow up again.

In the past, development of the loan portfolio quality was connected to the macroeconomic development and conditions. Figure 13 shows the comparison of the growth rates during the years 2002 and 2010. Clearly, since 2004 the receivables with default (non-performing loans[26]) have been going up, owing mainly to the sizeable growth in the loan portfolio, since 2008 also as a result of deteriorating macroeconomic conditions in the Czech Republic.

Figure 13: Comparison of growth rates



Source: ČNB, own calculation

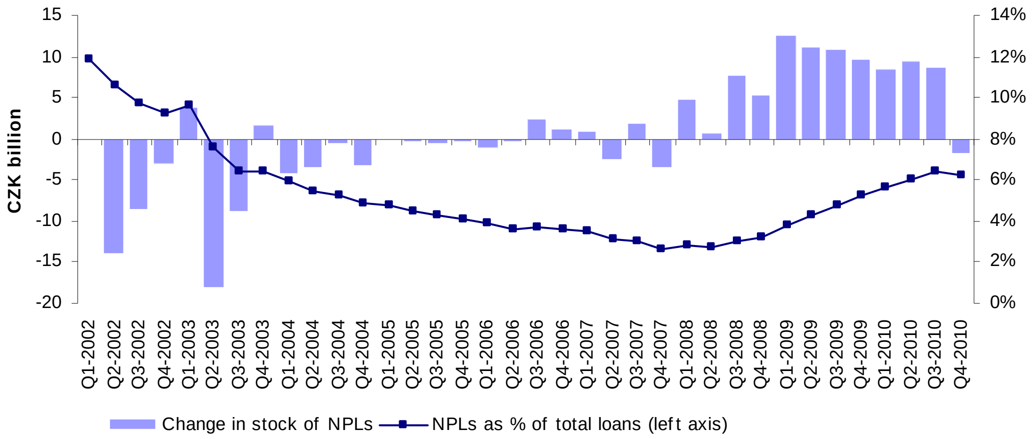
Notes: growth rates calculated as annual percentage change; growth rate in GDP calculated from index number (GDP Volume, 2005=100), growth rate of GDP for 2010-year end is an estimate based on the actual real data for third quarter of 2010

Loans without default (i.e. loans that fall into the category standard and watch) traditionally accounted for majority of the domestic banking sector's portfolio. As of December 2002, the non-defaulted loans created 91% of the loan portfolio; the percentage

[26] Loans with default (non-performing) are defined as substandard, doubtful and loss loans. Non-performing loans therefore include all loans that are past due for more than 90 days. See CNB Regulation No. 123/2007 for exact definitions.

of non-defaulted loans was gradually increasing with its peak in 2007 reaching 97.4% of total loans. Thus, over the period 2002-2007, the non-performing loans went down by more than 7 percentage points. At the end of 2010, loans without default amounted to 93.8% of total loans granted to residents and non-residents in the Czech banking sector and the share of non-performing loans created 6.2%.

Figure 14: Development of non-performing loans in the banking sector

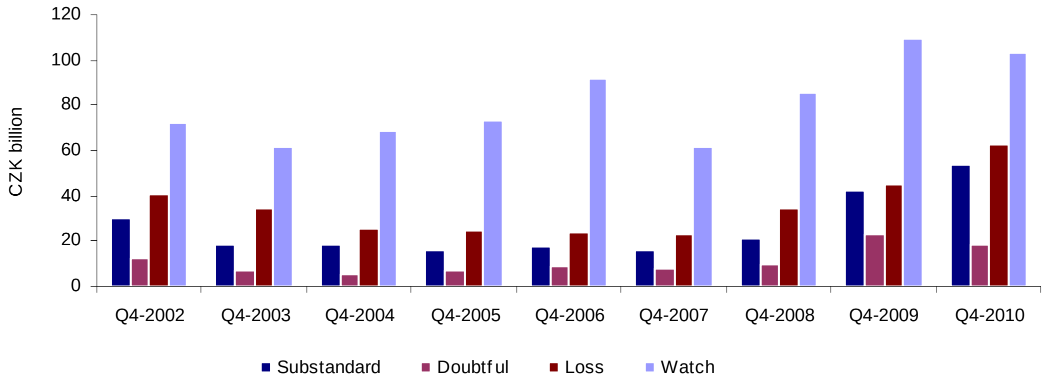


Source: ČNB

Figure 14 shows the development of the stock of **non-performing loans** over the relevant period together with its share in total loans. In the beginning of the period, the change in stock of non-performing loans is negative indicating the clean-up operations, as well as the share of non-performing loans in total receivables in sharply declining till the end of 2003. Over the years 2004-2007, the banking sector recorded stable trend in defaulted loans with average around CZK 50 billion, which amounted to approximately 4% of total loans. Starting with the third quarter in 2008 the loan portfolio started to deteriorate and the volume of defaulted loans has been creeping up.

As of December 2009, the non-performing loans amounted to CZK 110 billion, i.e. the volume doubled quickly over one year, and their share in total loans was 5.25%, up by 2.07 percentage points year on year. At the end of 2010, the volume of defaulted loans increased by additional CZK 24.7 billion to CZK 134.8 billion and its share in total loans amounted to 6.2%.

Figure 15: Loan portfolio quality



Source: ČNB

For the assessment of the credit risk in the banking system, several issues have to be taken into account. The development in non-performing loans has to be interpreted together with the development in the lending activity. As it is clearly visible form the Figure 13 and Figure 14 the loan portfolio quality started to deteriorate over the last two years. This is especially true in 2009, when receivables with default were growing up while the lending activity was slowing down.

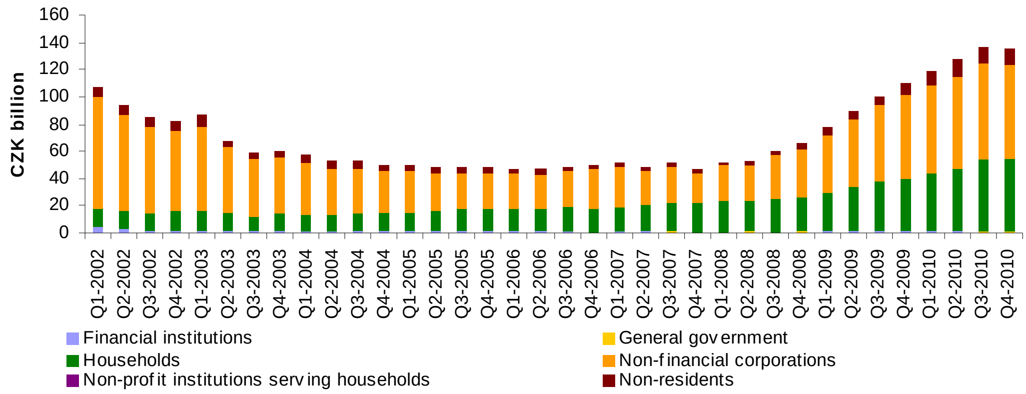
Secondly, the deteriorating loan quality is manifested in the increasing volume of classified loans.[27] Figure 15 shows the breakdown of classified loans in the domestic banking sector. The figure clearly reveals the deteriorating loan portfolio quality over the last three years, mainly indicated with the growth of loans in loss category.

In the beginning of the observed period, classified loans in the Czech banking sector amounted to CZK 155 billion with stable, slightly decreasing development. Classified loans reached its lowest point in 2007 with value around CZK 109 billion. However, since 2007 the loan quality portfolio started to deteriorate quickly. As of December 2009, the domestic banking sector recorded classified loans of CZK 220 billion, up by CZK 68.6 billion (45.4% growth year on year) compared to previous year. At the end of 2010, classified loans increased by another CZK 18 billion to CZK 237.6 billion. However, traditionally, the main part of the classified loans belongs to the lowest risk category, i.e. to watch loans. The growth in the lowest risk category (watch loans) over the last three years

[27] Classified loans are non-performing loans plus loans in the watch category.

(39% in 2008 and 28.4% in 2009 and 6.3% decrease in 2010 year on year growth) explains the majority of the rise in classified loans. The share of classified loans in total loans amounted at the end of 2010 to approximately 6.3%.

Figure 16: Structure of classified loans by economic sector



Source: ČNB

Figure 16 identifies **exposure of** the domestic banks to particular **economic sectors** over the selected period. The highest exposure concentration goes to the household and non-financial corporation sector over the whole period. This is in line with the trend in overall lending activity of the domestic banks, since the highest share of total loans belongs to those two economic sectors.

Over the period 2004 – 2007, the trend in development of defaulted loans did not differ much in the particular economic sectors. The **major exposure** was recorded in households sector (on average 1.5% of the loans granted) and non-financial corporations (on average 2.5% of the lending towards non-financial corporations). However, the share of non-performing loans within the lending activity to non-financial corporations was gradually decreasing over the period by approx. 2 percentage points.

Starting from 2008, the economic sectors recorded increase in the volume of defaulted loans.[28] Moreover, in 2009, all economic sectors recorded sharp increase in defaulted loans in absolute and relative terms. The highest increase in non-performing loans was recorded in non-financial corporation sector. The volume of defaulted loans rose by CZK 26.5

[28] With the exception of financial institutions sector, that recorded 9.5% decrease in defaulted loans compared to the year 2008.

billion y-o-y and their share in total loans provided to non-financial corporations was 7.9%. The volume of non-performing loans in the household sector increased by 1.11 percentage points (by CZK 13 billion) in 2009 and reached CZK 38.6 billion.

There are two issues that have to be mentioned when discussing the loan portfolio quality deterioration over the crisis years. First, as mentioned in CNB (2010), the increase in non-performing loans in the last decade can be influenced by prudential loan classification behaviour of the Czech banks. Especially in 2009, the banks voluntarily classified many obligations in the substandard category mainly on prudential basis. Threat of the financial crisis has led many banks to set the default classification threshold on a rather conservative level. Secondly, CNB (2010) pointed out that restructured loans (i.e. loans whose term has been modified, for example requested reduction in principal or interest payments due to deteriorating payment conditions of the borrower) are being classified as non-performing under the current regulatory rules. Although restructuring of a loan is some sort of partial default on the obligation, the term represents slightly different default than the typical “more than 90 days past due” default.

4 Literature overview

Literature overview covers some of the recent work conducted on the relationship between the development of non-performing loans and various factors (both macroeconomic and financial) that are supposed to have an impact on the loan portfolio quality.

On the international level, numbers of empirical studies investigating the link between macroeconomic factor and loan portfolio quality (namely measured as increase in volume of non-performing loans) have been published in recent years. The working papers published by central banks also attempt to incorporate some sort of sensitivity analysis or stress tests measuring the ability of the banking system to withstand some unanticipated shock.

The centre of the attention has been primarily focused on the growth of non-performing loans in the banking system, since NPLs are viewed as an important indicator of the loan portfolio quality. Worsening of the loan portfolio quality caused by an increase in non-performing loans may lead to efficiency problem for the whole banking sector. In extreme cases, the consequence of rapidly growing volume of NPLs in the banking sector is bank failure. From this point of view, monitoring and understanding the factors and determinants having an impact on the development of non-performing loans in the system is of utmost importance. Besides the NPL ratio, many authors used a different indicator of credit risk – such as the loan loss provisions, bank write-offs or default rates. The methodological framework applied to identify the potential risk factors varies accordingly to the variables used.

As a starting point in the **non-performing loan approach** can be seen the idea introduced by Blaschke *et al.* (2001). They proposed to take the NPL ratio (i.e. share of non-performing loans to total loans) as a credit quality indicator. The NLP ratio is interpreted as a default frequency measure and is regressed on various macroeconomic factors in order to obtain the sensitivity of bank borrowers to various relevant risk factors. Blaschke *et al.* (2001) included in the linear regression nominal interest rate, inflation rate, real GDP and terms of trade.

The **sensitivity approach** proposed by Blaschke *et al.* (2001) was further followed in the papers of Kalirai and Scheicher (2002) and Zeman and Jurča (2008). Kalirai and Scheicher (2002) investigated the credit risk in the Austrian banking system and based on the sensitivity test results they calculated credit exposure of the banking system towards changes of various macroeconomic factors. As a measure of the banks fragility they employed loan loss provisions (LLPs) mainly because of the unavailability of the data on non-performing loans. They concluded that the strongest impact on the LLPs is caused by nominal interest rates followed by industrial production, monetary aggregate M1, business confidence and the ATX stock exchange index.

Furthermore, Arpa et al. (2001) assessed the impact of macroeconomic development on risk provisioning and earnings of the Austrian banking sector. They argued that because of the nature of the banking business, commercial banks are exposed to some extend to the adverse impact of macroeconomic fluctuations. Moreover, they stressed the importance to monitor the impact of the macroeconomic conditions on the banking sector especially in the cases, when the unsoundness of the system is cause by the cyclical factors. The cyclical factors hit all the lending institutions and hence might be a dangerous source of systemic risk. They concluded that banks behave procyclically, i.e. they increase their risk provisioning in times of declining real GDP growth and in times of declining operating income. They also evaluated the impact of interest rates, real estate and consumer prices on the profitability of the banking sector.

The **single factor sensitivity analysis** applied on Austrian banking data was further developed by Zeman and Jurča (2008) who applied the same technique using different estimator on the Slovak banking sector. On the contrary to Kalirai and Scheicher (2002), they used the annual percentage change in NPL ratio as a dependent variable. As the most significant risk factors determining the development of the NPL ratio was indicated the real GDP, inflation, 3M BRIBOR and exchange rate SKK/EUR. In the multivariate regression model using the **cointegration technique** Zeman and Jurča (2008) attempted to construct a simple stress test. They evaluated the impact on the growth of NPL ratio – and in turn its impact on the balance sheets of the commercial banks – using the stand-alone changes in the underlying macroeconomic variables (sensitivity test) as well as simultaneous changes in all variables (scenario based on a historical event). Finally, using the scenarios they evaluated the resilience of the Slovak banking sector towards economic slow-down and monetary policy shock.

Sorge and Virolainen (2006) provided an exhaustive review of the current state of the macro stress testing practices and methodologies. Beside the review, they also conducted a macro stress testing exercise applied on the banking sector in Finland. Using the **macroeconomic credit risk model** they explored the relationship between macroeconomic variables and the corporate sector default rates. The credit risk measure – probabilities of default in the individual corporate sectors – was modeled as a logistic transformation of the set of individual industry-specific variables and macroeconomic variables. The macroeconomic variables selected in the model were the GDP, interest rates (both nominal and real) and level of corporate indebtedness measured as gross debt in that particular industry. They concluded that GDP is positively related to the industry-specific macroeconomic indices and the corporate indebtedness is negatively related with them. The interest rates performed poorly and were insignificant. Having obtained a coherent credit risk model, Sorge and Virolainen (2006) conducted a stress test using a negative shock in GDP and a sudden short-term interest rate increase. They used the results obtained on a fictive credit portfolio representing the aggregated loan portfolio in Finland to evaluate the pros and cons of the macro stress testing methodologies.

Similarly, Lehmann and Manz (2006) run a **panel regression model** of various bank balance sheet components of earnings (such as net income, provisions, write-offs and earnings from trading and commission business) of the Swiss banking sector on selected macroeconomic variables plus some individual bank specific control variables. The main aim of their study was to identify the major macroeconomic factors having an impact on the profitability of the Swiss banks. Furthermore, they also conducted a stress test exercise to quantify the impact of those factors. As far as the credit risk is considered in the paper, Lehmann and Manz (2006) used the provisions as a proxy for the realized loss in the banking sector. They employed the logit transformation[29] of provision ratio as a dependent variable and three macroeconomic explanatory variables (GDP growth, unemployment rate, 3M interest rate) and one financial variable (spread of corporate over government bond yields). The results confirmed that economic growth has negative impact on the loan portfolio quality, since lower GDP growth contributes to increase in provisions. Also higher unemployment rate and higher interest rates increased the provisions and hence have are related negatively to the loan portfolio quality.

A parsimonious model employing the **vector autoregression (VAR) methodology** was used by Hoggarth, Sorensen and Zicchino (2005) for the aggregated data on UK-owned

[29] Logit transformation can be expressed as logit (x) = ln(x/(1-x)) and represents a non-linear relationship between the credit risk indicator and the explanatory variables.

banks. The authors used the banks' write-offs as a measure of credit risk. They constructed various vector autoregression models – on the aggregated level, on the sectoral level and finally also a household model. The selected explanatory variables varied accordingly to the model. For the aggregate write-off model, the authors used the output gap, retail price inflation, nominal short-term interest rate and aggregated write-offs as variables in the VAR model and examined the impact of changes in the underlying macroeconomic variables on the banks' aggregate losses. They found a significant relationship between change in output gap and the write-off ratio. Increasing output gap caused the banks' write-offs to fall after some time lag. Furthermore, the results indicated that inflation is correlated negatively with banks' write-offs. And finally, unexpected increase in interest rates caused an increase in banks' write-offs after some time lag.

A VAR methodology to identify causal relationships between NPL ratio and various macroeconomic factors and to assess the resilience of the banking sector was used in the working papers published by the central banks of Jamaica and Ghana. Amediku (2006) estimated the impact of changes in real effective exchange rate, imports, inflation, interest rate and the output gap on the NPL ratio of Ghanaian banking sector. Tracey (2006) conducted the same analysis for the banking sector of Jamaica using real effective exchange rate, CPI index, terms of trade, aggregated loan stock, 180-day Treasury bill rate and growth of monetary aggregate M1.

Also Filosa (2007) investigated the resilience of the Italian banking sector towards various macroeconomic factors using the VAR approach. Besides the standard application of macro stress test, Filosa (2007) was interested in investigating two issues: whether and to what extend does the procyclical character of financial risk influence the banks' soundness, and what is the impact of unexpected tightening of monetary policy on the banks' soundness. He constructed three VAR models that differ only in the banks' soundness indicator: change in stock and flow of non-performing loans and the interest margin to outstanding loans. The endogenous variables chosen in the models were the output gap, inflation, spread between loan and deposit rate and the amount of free capital held by banks. He concluded that despite the fact, that financial risk is procyclical, the procyclical feature of the business cycle doesn't have a significant effect on non-performing loans and the interest margin in the Italian banking sector. He found out that the dynamics of the NPL ratio is explained mainly by its own shocks.

As far as the **Czech banking sector** is considered, Babouček and Jančar (2005) run unrestricted VAR model over the time horizon of 11 years (Oct 1994 till Nov 2004). The authors used NPL ratio as a measure of credit quality indicator. However, they emphasized the drawbacks of using NPL ratio as an indicator of quality, namely the fact that non-performing loans tend to be a lagging indicator of loan portfolio quality. From this point of view, the bankruptcy or default rates might be a better indicator of banks fragility. Babouček and Jančar (2005) included in the VAR model number of macroeconomic variables: monetary aggregate M2 as a proxy for GDP, real effective exchange rate, imports and exports, aggregate banks loan, unemployment rate, inflation and interest rates (PRIBOR). To control for structural breaks in the non-performing time series caused by changes in classification or by the clean-up rounds[30] six dummy variables were introduced in the model.

Babouček and Jančar (2005) investigated the impulse response results of the unrestricted VAR model and presented 45 responses that express economic theories or empirical findings. Their simulation supported majority of the basic hypotheses and Babouček and Jančar (2005) hence concluded that the Czech banking sector "reflects cross-country similarities in banking systems".

Similarly to Babouček and Jančar (2005) also Festić and Romih (2008) attempted to find evidence on macroeconomic factors influencing the growth of non-performing loans in the Czech Republic, Slovakia and Slovenia. For the Czech banking sector they constructed a VAR model containing 8 endogenous variables – besides the NPL ratio, a long-term real interest rate, exports, unemployment rate, harmonized CPI index, stock exchange index, real effective exchange rate and real investment. As a result to the impulse response investigation, they found 4 responses supporting the underlying economic theory: increasing unemployment causes deceleration of NPL ratio, rising export improves the loan portfolio quality, lower inflation levels decelerate the growth of NPLs and higher equity prices improve the loan portfolio quality.

[30] As part of the privatization process banks were cleaned up from their bad loans. Major rounds of clean-ups appeared in the beginning of 1990s with large banks continuing in the second half with the shift to smaller banks.

5 Empirical analysis

Following part represents the core analysis of the thesis. In the first part, the significant macroeconomic risk factors and their expected relation towards the growth of non-performing loans are described and the following part focuses on empirical application. The latter part also aims to forecast the most likely development of the loan portfolio and assess the loan portfolio quality.

5.1 Data sources and availability

All data used in the following parts of the thesis have been collected from various sources. The thesis employs monthly data on the aggregate banks' loan portfolio in the Czech Republic obtained from ARAD[31], a public database of the Czech National Bank. The data on client loans are reported in nominal values and correspond to loan balances[32] of the commercial banks in the Czech Republic. Data on non-performing loans are available starting from 2002.

Financial data on interest rates (various maturity PRIBOR contracts), oil price (NYMEX Light Sweet Crude), the Prague Stock Exchange index and CPI index were obtained from Bloomberg. Monthly averages of the foreign exchange rates were taken from the Czech National Bank.[33]

The remaining employed data on GDP, industrial production, exports, imports, unemployment rate and monetary aggregates were obtained from the International Financial Statistics database (International Monetary Fund).[34]

5.2 Identification of significant risk factors and their expected relation to the credit risk factor

In this section we are trying to find a relation between a measure of credit risk and various macroeconomic factors and identify the significant macroeconomic factors. The transmission channels investigated later in the empirical analysis require some statement about the relation of the selected variables to the credit risk factor. This section follows the

[31] http://www.cnb.cz/docs/ARADY/HTML/index_en.htm

[32] The loan balances are defines as closing balances of client loan accounts, i.e. initial balances plus drawings of new loans minus installments/repayments of any loans granted earlier.

[33] http://www.cnb.cz/en/financial_markets/foreign_exchange_market/exchange_rate_fixing/daily.jsp

[34] http://www.imfstatistics.org/imf/

grouping of the variables presented in Kalirai and Scheicher (2002) or Zeman and Jurča (2008) and attempts to find the sensitivity of the quality of the loan portfolio towards various factors.

1. Cyclical indicators

Cyclical indicators category relates to indicators, which characterize the overall economic activity and relate therefore directly to the general economic activity. Over the business cycle many macroeconomic variables show some co-movements with the economic cycle. Typically the direction of the movements of macro variables is either procyclical, countercyclical or acyclical.

GDP is the basic cyclical indicator of the economic activity. It is assumed, that the loan portfolio quality depends on the business cycle and the development of the economic activity. In recession, the economic activity falls and the deteriorating activity in turn negatively affects the profitability of the firms. Decreasing income and rising payment difficulties in the recession plus decreasing profitability of the corporate sector together with often rigid wages lead to rising unemployment and asset prices, this in turn leads to worsening of the loan portfolio quality. Conversely, rising income caused by the favourable economic development improves the ability of the borrowers to service debt and hence leads to lower growth in non-performing loans.

Similarly, industrial production is a procyclical and coincident indicator of the economic activity; moreover, industrial production growth often leads to GDP growth cycle (Kalirai and Scheicher, 2002). Increase in industrial production anticipates the economy in growth phase; hence loan portfolio quality should improve. Therefore, GDP and industrial production are expected to be related negatively with NPL ratio.

2. Price stability indicators

Typical measure of price stability included often in the models of univariate regressions[35] performed by the central bankers is the consumer price index as indicator for inflation. Kalirai and Scheicher (2002) argue that higher inflation may indicate the economy is operating above its potential and hence may be overheating. On the other hand, higher inflation helps the borrowers to repay their obligations, since it reduces the real value of

[35] See Kalirai and Scheicher (2002) for the single risk analysis of the Austrian banking sector or Zeman and Jurča (2008) for the analysis of the Slovak banking system.

the outstanding debt. Following the Fisher equation, higher inflation reduces the value of real interest rates and hence lowers the direct cost of borrowing and encourages economic activity. Similarly, decreasing inflation may indicate the cool-down of the economy and increases the real interest rates. Increase of real interest rates has negative impact on the loan portfolio quality, since increase in costs of borrowing will cause loan defaults in corporate sector and households Hence, inflation is expected to be related negatively with the growth of non-performing loans in short-term (Kalirai and Scheicher, 2002; Zeman and Jurča, 2008).

However, over the longer time horizon, lenders know that inflation will decrease the value of their claims and money, so they increase the interest rates in order to compensate for the loss in value.

Moreover, Festić and Romih (2008) claimed that lowering inflation causes lowering NPL growth. They argue that high inflation level makes the macroeconomic environment less transparent and hence leads to worsening of the loan quality portfolio.

Also, Tracey (2006) argues that rising inflation creates less transparent macro environment and hence contributes to rising information asymmetry on the side of credit institutions. This in turn leads to adverse selection in banks when providing the loans to clients, and hence to increase in bad loans.

The quantity theory of money assumes a direct link between monetary aggregate and the inflation. That is why monetary aggregate is often also included as a price stability indicator. Moreover, Babouček and Jančar (2005) are using real money as a proxy for GDP.

3. Household indicators

Unemployment rate serves as household indicator directly related to the situation in the household sector. As it was presented in chapter 3 lending to household sector increased dramatically in the recent years – the share of loans to households (both individuals and trades) in total loan portfolio increased from 20% in 2002 to almost 47% at the end of 2010. Thus, because of the significance of the household sector in the loan portfolio, unemployment rate was included in the analysis.

Generally, with higher disposable income available to households, the economic conditions of households improve and therefore the loan portfolio quality increases. With higher unemployment, households are expected to encounter difficulties when repaying their obligations and the loan portfolio quality worsens. Increasing unemployment thus positively contributes to the increase of non-performing loans.

4. Financial market indicators

Financial market indicators outline the situation in financial markets. Indicators included in the analysis usually consist of nominal and real interest rates and the stock price index. In case of the Czech Republic the official index of the Prague Stock Exchange - stock market index PX.[36]

The key financial market indicators are the interest rates, since they represent the direct costs of borrowing. The higher the cost of borrowing the greater the possibility of loan defaults by firms and households, as they encounter difficulties to repay their obligations. The interest rate considered later in this study is the 3-month PRIBOR (Prague Interbank Offered Rate). Increase in interest rates is assumed to have negative impact on the loan portfolio quality.

Stock market indices are typically assumed to be the leading indicators of the economic activity. Stock markets are forward-looking because the behaviour of the market participants reflects their future expectations and expected future earnings. These indicators hence tend to move before the economy and will often rise even before the respective economy recovers from recession. Rising stock markets often indicates a period of economic expansion and therefore the quality of the loan portfolio will improve.

5. External indicators

External indicators refer to a category of factors that do not originate in the domestic economy, but can have important impact on the domestic financial system. These factors are usually related to international foreign trade, such as exchange rates, oil prices and terms of trade or volume of traded goods.

A small open economy can be significantly impacted by the changes in export, as export is usually an important part of the gross domestic product. Rising export contributes to GDP

[36] The PX index is the official index of the Prague Stock Exchange. The PX index was calculated for the first time on March 20, 2006 and replaced the former index PX 50.

growth and positively affects export-oriented firms, which in turn results in better repayment condition in the export-oriented sectors and the loan portfolio quality is expected to improve (Kalirai and Scheicher, 2002).

On the contrary, oil price expresses direct costs for major part of the corporate sector and hence can have a negative impact on the loan portfolio quality. An increase in oil price leads to negative demand shock and the energy costs of households and businesses increase, this leads to worsening of the repayment conditions and thus to increase in bad loans (Kalirai and Scheicher, 2002).

The impact of foreign exchange rates on the loan portfolio quality is ambiguous. Depreciation of the domestic currency may stimulate exports and the production of import-competing goods in the country, which can have a positive effect on the loan portfolio quality. Moreover, depreciation of the local currency would improve the position of the borrowers, since it means that borrowers are obliged to repay less than the initial value of the loan. However, depreciation of the domestic currency causes also an increase in the imported goods and hence may harm importers. Also, depreciation of the domestic currency will have exactly reverse effect if the borrowers are primarily borrowing in foreign currency (Kalirai and Scheicher, 2002).

Figure 17: List of risk factor and their expected relation to the quality of loan portfolio

Group	Variable	Expected relationship to the growth of NPLs
Cyclical indicators	GDP, Industrial production	negative / -
Price stability indicators	Inflation, monetary aggregate	ambiguous +/-, negative / -
Household indicators	Unemployment rate	positive / +
Financial market indicators	3M PRIBOR	positive / +
Financial market indicators	PX index	negative / -
External indicators	Exports	negative / -
External indicators	Oil price	positive / +
External indicators	Exchange rates	ambiguous +/-

5.3 VAR model

5.3.1 Introduction to VAR models

Vector autoregression model were first introduced by macro-econometrician Christopher Sims in 1980s as a framework to model and describe the dynamic interrelations between stationary variables. Since then, vector autoregression models have been used to model joint dynamics and causal relations among various sets of macroeconomic variables.

In order to formalize the VAR approach, let's consider a time series that consists of observations $\{Y_t, t \in T\}$, where T is a time index set, and considered realizations of a random variable that can be described by some stochastic process.

A **univariate autoregression** equation can be formalized as follows[37]:

$$Y_t = \alpha + a_1 Y_{t-1} + a_2 Y_{t-2} + a_3 Y_{t-3} + \ldots + a_p Y_{t-p} + e_t$$

where e_t denotes serially uncorrelated innovation with zero mean and constant variance. This process is also known as autoregressive process of order p (AR*(p)* process). The AR*(p)* process hence describes the dynamics of just one random variable as a function of its own past realizations.

Yet, since macroeconomic variables often interact with each other the vector autoregression models are used in order to capture rich dynamics in multiple time series. The advantage of the vector autoregression models is their ability to capture the dynamic relationships between variables. VAR models are a system of linear equations, where each variable enters the system symmetrically without any presumption about their dependence or independence in the model. More to the point, every variable in the system is affected by its own past values and past values of the remaining endogenous variables.

Definition of reduced form vector autoregression model of order *p*[38]

An n-dimension vector autoregression model of order p, VAP(p), is a system of n linear equations with n variables $\{Y_{it}, t \in T, i \in 1, 2, \ldots n\}$, where each equation describes the dynamics of one variable in the whole system. The dynamics of each variable is explained as a linear function of its own lagged values (p lags) and previous p lags of the remaining n-1 variables.

VAR(p) with n-variables $\{Y_{it}, t \in T, i \in 1, 2, \ldots n\}$ is a system of equations:

$$y_t = c + A_1 y_{t-1} + A_2 y_{t-2} + \ldots + A_p y_{t-p} + u_t$$

Where

[37] See Green (2003) and Verbeek (2004) for further technical details

[38] See Lütkepohl (2005), chapter 2

$y_t = (y_{1t}, y_{2t}, \ldots y_{nt})'$ is a $(n \times 1)$ vector of random variables, $A_t = (A_1, A_2, \ldots A_p)'$ are $(n \times n)$ coefficient matrices, $c = (c_1, c_2, \ldots c_n)'$ is a $(n \times 1)$ vector of intercept terms, and $u_t = (u_{1t}, u_{2t}, \ldots u_{nt})'$ is a *n*-dimensional innovation process, *i.i.d.* with zero mean.

A reduced form of a VAR model is expressed as a system of equations where each variable is expressed as a linear function of its own past values, past values of all the remaining variables in the system and serially uncorrelated error term. This system can be understood as a system of AR(*p*) processes taken in more variables that contains lagged valued of each variable in each process. Each equation in the system can be estimated using ordinary least squares (OLS), since the right-hand-side of the equation system consists of predetermined variables and the error terms are white noise. Because of the symmetrical property of a reduced form VAR model, the OLS estimator produces consistent and asymptotically efficient estimates. The error terms are serially uncorrelated but correlated across equations.

Vector autoregression models can be divided into three types – a reduced form, recursive form and structural form of VAR. The error terms in recursive VAR model are constructed as uncorrelated in each regression with error terms in the preceding equations. This can be obtained by adding some contemporaneous values as regressors in the equations. Each equation can be estimated via OLS and the residuals are uncorrelated across equations. However, results obtained by this approach heavily depend on the order of the variables in the equations. Changing the order of VAR equations changes the coefficients and residuals. This approach is very computational burdensome for large models, since there are *n!* possible orderings in a *n*-equation VAR system (Stock and Watson, 2001).

Finally, the structural VAR requires some economic theory that is necessary to sort out the contemporaneous links among the variables. The structural form VAR cannot be estimated using the standard techniques since the variables are correlated with error terms. Hence, because of the problem of endogeneity, structural VAR models are estimated using instrumental variables regressions and require identifying assumptions in order to model the causal links among the variables (Stock and Watson, 2001).

5.3.2 Characteristics of VAR models

Vector autoregressive models gained popularity because of their easy implementation – because of the symmetric property of the reduced VAR model, the system can be estimated easily by applying ordinary least squares.

Drehmann (2008) showed that macroeconomic models usually follow three main objectives: *validation* – description and summarization of the data, *forecast performance* – to make macroeconomic forecasts and *communication* – to advise policymakers. Vector autoregressive models usually do outperform more complicated techniques in the data description and forecasting task, however, they are not well suited for communication purpose.

As vector autoregressive models contain current and lagged values of multiple time series – macroeconomic variables – they capture co-movements in the variables over time better than bivariate regression models. Standard techniques used in the data generating process in VAR analysis (such as the impulse response functions) allow interpreting the co-movements in the variables easily. Moreover, VAR models allow the macroeconomic variables to "talk about themselves" without any constraints or restrictions imposed by the economic theory. Small-scale VAR models can outperform the classical macro models in forecasting task (or represent a proper benchmark to those models), however, when adding additional variables and/or allowing for time-varying parameters the estimation procedure becomes rather complicated, since adding variables dramatically increases the number of parameters to be estimated[39] (Stock and Watson, 2001).

VAR models may lead to better results than simultaneous equations, which depend on the economic theory. On the other hand, the reason why VAR models are criticized is exactly their ad hoc specification. Since they often do not depend on the economy, they hardly shed a light on the structure of the economy.[40] More to the point, there is no clear procedure when choosing the proper variables into the model. This is exactly a major drawback when the causal relations between the variables have to be examined for communication purpose.

[39] A VAR model with *n* equations and *p* lags requires to estimate $n+(n^2p)$ unknown coefficients including the intercepts.

[40] Structural VARs aim to examine the causal relations between the macro variables. However, reduced form VAR models are not capable to estimate all parameters of the structural VAR without further necessary identification restrictions.

5.3.3 Selection of variables and data description

In this section we will describe the selected endogenous variables that enter the reduced form VAR model described later in this chapter. The selection of suitable set of variables in the model is always a main concern in every econometric analysis. Firstly, the selection of the variables was inspired by the reviewed literature and published papers investigating similar transmission mechanisms and employing similar methodology.

When considering VAR analysis on credit risk the most frequently investigated variables include GDP, monetary aggregates, loans granted to corporate sector and/or households, CPI index, unemployment rate, real effective exchange rate, exports, imports, terms of trade and some indicator of the loan portfolio quality itself (such as NPL ratio, loan loss provisions, default rates etc.).

The following analysis has been inspired mainly by the work conducted by Babouček and Jančar (2005) on the loan portfolio quality data for the Czech Republic. Similarly to their work, the main transmission channels for the evolution of the defaulted loans were taken into account and the macroeconomic variables were chosen accordingly. To reflect the competitiveness of the economy of the Czech Republic data on exports, real GDP and CZK/EUR exchange rate were included in the analysis. Secondly, the real sector is defined by interest rate, inflation and the quality of the banks' loan portfolio and finally, the utilization of the domestic capacities is expressed by the unemployment rate and aggregated loans.[41]

Monthly data spanning from January 2002 to December 2010 were used. Monthly data on all variables included in the analysis are readily available from most public databases with the exception of GDP figures. In order to obtain monthly data on real GDP growth, the Chow-Lin procedure to convert quarterly observations to monthly interpolations was used. The quotation of exchange rates follows the standard quotation. The base currency is the Czech crown (CZK). The exchange rate is expressed as amount of quoted currency per one unit of the base currency, i.e. the amount of EUR per one CZK.

[41] The model was estimated using various other macroeconomic variables: industrial production was tried as proxy for GDP, the exchange rate CZK/USD was used as replacement of CZK/EUR exchange rate, imports, oil price and PX index were included as explanatory variables into the model. However, the best results were obtained using the above mentioned variables.

Figure 18: Description of original time series

Time series	Denotation	Units	Data span	Note
NPL Ratio	NPL_ratio	%	2002 M1 – 2010 M12	$\frac{Subst + Doubtful + Loss}{Total\ loans}$
Aggregated Loans	Total_loans	Bn CZK	2002 M1 – 2010 M12	Nominal value
Real GDP	GDP_real	Constant prices (base year 2005)	2002 Q1 – 2010 Q4	Seasonally adjusted
Exports	Exports	Bn CZK	2002 M1 – 2010 M12	Seasonally adjusted
3M PRIBOR	PRIBOR	%	2002 M1 – 2010 M12	Monthly average
Unemployment rate	U	%	2002 M1 – 2010 M12	Seasonally unadjusted
Consumer price index	CPI	% (base year 2005)	2002 M1 – 2010 M12	Seasonally unadjusted
CZK/EUR exchange rate	CZK_EUR	Amount of EUR per 1 CZK	2002 M1 – 2010 M12	Monthly average

Descriptive statistics together with the plot of the original time series can be found in the Appendix in Figure 27 and Figure 28.

5.3.4 Stationarity in time series

In order to continue in investigation of the time series data using the VAR approach, the time series have to be stationary. Stationarity of the time series is especially important when considering the effects of shocks on the adjustment path of the various variables in the model. Non-stationary processes (such as random walk for example) have an infinitely long memory and the shock will permanently affect the process, while in models with stationary time series the effect of the shock is only temporary (Verbeek, 2004).

When working with time series, it is very helpful to display the data graphically, since a visual inspection of the development of the time series can reveal potential problems. Generally speaking, if a time series does not seem to return to a constant value (mean) or have a constant variance, then most likely the time series is not stationary.

Original time series are plotted in Figure 28 in the Appendix. As it is clearly visible from the graphs, many macroeconomic variables are often generated by non-stationary process and follow some stochastic trend.

Definition of weak stationarity[42]

The time series that consists of observations $\{Y_t,\, t \in T\}$ where T is a time index set is said to be stationary if:

(I) $E\left(Y_t^2\right) = \sigma_y^2 < \infty \; \forall t \in T$

(II) $E\left(Y_t\right) = \mu \; \forall t \in T$

(III) $Cov\left(Y_s, Y_t\right) = Cov\left(Y_t, Y_{t+h}\right) \quad \forall s, t, h \in T$

In other words, stationary time series exhibit three features: they have finite, constant and positive variation, constant mean and covariances of the data series do not depend on the time period in which they are observed, i.e. they are invariant to a time shift.

When identifying non-stationary time series, it is useful to plot the time series in levels and its correlogram. Correlogram represents graphical inspection of stationarity of the time series. It refers to the autocorrelation function[43] (ACF) that models the dependencies among observations and describes the process of evolution of the time series over time. The ACF shows to which extend there is a correlation among the realizations and thus shows the length and strength of the memory of the time series over time. Generally speaking, the correlogram of a stationary time series diminishes quickly with growing lag order.

Non-stationarity of the time series can arise from various sources, but the most important is the presence of the so-called unit roots in the time series. Visual inspection of the autocorrelation function can reveal the presence of unit roots in the time series, when the ACF on the first lag close to 1, the time series has a unit root. The ACF graph of all endogenous variables showed highly probability of the presence of unit roots and hence the most likely non-stationarity of original time series. However, visual examination of the ACF function is rather an auxiliary tool in determining the presence of unit roots. In order to test the presence of unit roots in the time series, the Augmented Dickey-Fuller test (ADF test) was conducted for all original time series.

[42] See for example Green (2003), pp. 612

[43] Autocorrelation function of a time series Y_t can be formalized as following:

$\rho_k = \dfrac{\operatorname{cov}(Y_t,\, Y_{t-k})}{\operatorname{var}(Y_t)}$, i.e. the process of the evolution of a time series is described by its mean and variance.

Figure 19: Summary of the ADF test results – original time series

Variable	Test statistics	p-value
NPL_ratio	-0.6131	0.9779
Total_loans	-1.9822	0.6105
GDP_real	-1.3890	0.5892
Exports	-0.7999	0.8187
PRIBOR	-1.8590	0.3522
U	-1.5410	0.5129
CPI	0.3411	0.9794
CZK_EUR	-1.0830	0.7249

Notes: Under null hypothesis the time series has a unit root and is non-stationary, regarded as stationary if the null hypothesis is rejected. Optimal number of lags was chosen according to the information criteria. For details see Figure 29 in the Appendix.

The ADF test for the original time series reveals that all time series are non-stationary in their level values. This is of no surprise, as all the original time series clearly contain a trend. Hence, the time series have been transformed into first differences or monthly percentage changes in the original values.[44] The transformation is employed because it often transforms a non-stationary time series into stationary. Transformation into absolute differences and monthly percentage changes was preferred to differences in logarithm, even though this is practically equivalent to the percentage change and is often used for macroeconomic variables. The reason is that the examined sample contains the data observed during the financial crisis (2009 M1 – 2009 M12)[45] and hence the changes in the variables are sometimes very large. As mentioned in Babouček and Jančar (2005) the log transformation can produce a significant downside bias in the forecasts and simulation when the changes in the variables are large.

[44] Transformed time series are used in order to avoid the problem of spurious regression.

[45] The time range corresponds to the time, when the Czech Republic was hit by the financial crisis. According to NBER, the financial recession spanned from 2007 M12 – 2009 M6.

Figure 20: Description of transformed time series

Time series	Denotation	Data span	Note
NPL Ratio	d_npl	2002 M2 – 2010 M12	$NPL\_ratio_t - NPL\_ratio_{t-1}$
Aggregated Loans	d_L	2002 M2 – 2010 M12	$\frac{Total\_loans_t - Total\_loans_{t-1}}{Total\_loans_{t-1}}$
Real Gross Domestic Product	d_GDP	2002 M2 – 2010 M12	Growth of real GDP obtained using Chow-Lin procedure for interpolation[46]
Exports	d_EX	2002 M2 – 2010 M12	$\frac{Exports_t - Exports_{t-1}}{Exports_{t-1}}$
3M PRIBOR	d_pribor	2002 M2 – 2010 M12	$PRIBOR_t - PRIBOR_{t-1}$
Unemployment rate	d_U	2002 M2 – 2010 M12	$U_t - U_{t-1}$
Consumer price index	d_cpi	2002 M2 – 2010 M12	$\frac{CPI_t - CPI_{t-1}}{CPI_{t-1}}$
CZK/EUR exchange rate	d_eur	2002 M2 – 2010 M12	$\frac{CZK\_EUR_t - CZK\_EUR_{t-1}}{CZK\_EUR_{t-1}}$

Notes: The original time series has been transformed into growth rates.

Descriptive statistics as well as graphs of the transformed time series can be found in the Appendix in Figure 30 and Figure 31.

Figure 21: Summary of the ADF test results – transformed time series

Variable	Test statistics	p-value
d_npl	-3.0060	0.0344
d_L	-1.4084	0.1483
d_gdp	-2.4183	0.0156
d_EX	-2.7400	0.006
d_pribor	-5.4068	5.13E-09
d_U	-1.7653	0.0737
d_cpi	-8.3406	1.87E-23
d_eur	-7.9580	6.54E-20

Notes: Under null hypothesis the time series has a unit root and is non-stationary, regarded as stationary if the null hypothesis is rejected. Optimal number of lags was chosen according to the information criteria. For details see Figure 32 in the Appendix.

All series are non-stationary in levels, however, their transformed version is stationary with exception of the time series of total loans. For *d_L* the ADF test failed to reject the null hypothesis of presence of the unit roots. Nevertheless, for this variable, the ACF didn't show the presence of unit root. More to the point, stationarity tests are often subject to a critique regarding their low power especially when finite (small) sample of data is considered (see for example Cochrane, 1990).

[46] Real GDP growth rates were obtained employing toolbox for Chow-Lin temporal disaggregation to disaggregate quarterly growth of GDP using monthly growth rates of seasonally adjusted industrial production, exports and imports. For further technical details see Chow and Lin (1971).

In order to investigate the stationarity of *d_L*, another stationarity test, the Kwitlowski, Phillips, Schmidt, and Shin test (KPSS) has been performed. Opposite to the ADF test, the KPSS test checks the null hypothesis of observed time series being stationary around a deterministic trend against an alternative of a unit root.[47] Whereas the ADF test failed to confirm stationarity of *d_L*, the KPSS test showed the *d_L* time series is stationary.

It is worth mentioning that similarly to the Augmented Dickey-Fuller test, the KPSS test has a relatively low power when dealing with short time series. More to the point, the time series of non-performing loans and aggregated loans might be affected with structural breaks, nevertheless for the purpose of following investigation, we will assume, all transformed time series are stationary.

5.3.5 Model description

In this section, a reduced form VAR model will be described and estimated. The VAR model examined has a symmetric structure that supports the application of OLS estimator. Moreover, OLS estimation of the symmetric reduced form VAR model yields consistent and asymptotically efficient coefficient estimates.

The reduced form vector autoregression model can be formalized in the matrix notation as following:

$$\Delta Y_t = c + \sum_{i=1}^{p} A_i \Delta Y_{t-i} + u_t \text{ , where}$$

p denotes the optimal (examined) length of lags

Δ denotes the monthly percentage change, measured in percentage points

Y_t is a a (8×1) vector of endogenous variables

$A_t = (A_1, A_2, \ldots A_p)'$ are (8×8) coefficient matrices

$c = (c_1, c_2, \ldots c_n)'$ is a (8×1) vector of intercept terms and

$u_t = (u_{1t}, u_{2t}, \ldots u_{nt})'$ stands for a 8-dimensional innovation process, *i.i.d.* with zero mean.

The critical specification issue in the vector autoregression models is the selection of the optimal lag length of the endogenous variables. Lütkepohl (2005) shows how

[47] For further technical details see Figure 33 in the Appendix.

misspecification of the VAR model impacts its outcome: over-fitting (i.e. selection of higher lag order than optimal) reduces the forecast precision of the VAR model; similarly, under-fitting of the model may generate autocorrelated errors. There exist several criteria and statistical test, such as minimizing one of the commonly used information criteria, which can help to detect the optimal lag length of the VAR model. However, Lütkepohl (2005) also points out that choosing the optimal lag length might not be desired when the model was constructed for some specific purpose (often for example when constructing models for prediction of the variables and hence the selected lag length has its economic interpretation).

Typically, the way how to find the most parsimonious model is examination of the information criteria, such as Akaike's Information Criterion (AIC) and Schwarz Bayesian Criterion (BIC), Hannah-Quinn Criterion (HQ) etc. Models with a lower information criterion are typically preferred, as the criteria add a penalty with increasing number of regressors in the model.

The optimal lag length of the endogenous variables was calculated using the AIC, HQ and Final Prediction Error.[48] All three criteria revealed that the optimal lag length for the examined model is 11. As pointed out in Baboček and Jančar (2005), in order to deal with the effects and reactions when macroeconomic variables are considered, usually three to four quarters are examined. This would in our case mean a lag structure including 9-12 lags on endogenous variables, which is consistent with the optimal lag length obtained by the information criteria.

However, as mentioned previously, the number or parameters that have to be estimated increases rapidly with increasing number of endogenous variables and/or number of their lagged values, thereby leading quickly to problems with insufficient degrees of freedom and thus even preventing the estimation. Because of short time series that are available for the examination, the lag structure of the model would have to compromise the data constraint with the requirement of sufficiently long lag structure of the model.

The best results were obtained employing the lag order of 4, moreover, considering monthly time series, four lagged values of the endogenous variables correspond to a rough

[48] For technical details and comparison of the information criteria see Lütkepohl (2005), pp. 146-157

quarter movements. Even though, the data constraints do not allow considering the full lag structure, taking into account changes in quarters can reveal some important relationships between the variables. When employing lag structure of 4, the model contains 32 lagged explanatory variables, which amounts to 30% share in the sample of observations. According to Babouček and Jančar (2005), the model is over-fitted when the share exceeds one third of the size of the set of observations.

5.3.6 Econometric results

The regression output[49] can be found in Figure 34 in the Appendix. The table tries to summarize in a transparent manner the regression output of the VAR model by displaying the estimated coefficients and the standard statistics of the model. The table also displays the standard R^2 measures for each of the system equations, since each equation is estimated by least squares.

The model contains 264 coefficients that have to be estimated. According to the standard econometric conventions in displaying the significance expressed by t-statistics and its corresponding p-values, the results clearly show, that there are only 51 (i.e. approx 19%) significant coefficients of the endogenous variables in the model. The remaining coefficients are insignificant on the conventional significance levels.

However, as pointed out in Lütkepohl (2005), because of the dynamic structure of the VAR model it is difficult to interpret the coefficients of variables as elasticities between its endogenous variables. More to the point, Sims (1980) claimed that the estimated coefficients in the VAR model "tend to oscillate" and usually involve some "cross-equation feedbacks", and thus it is extremely difficult to make sense of the individual coefficients or its signs in the individual regression equation.

And finally, Babouček and Jančar (2005) obtained similar results with regard to the significance of the coefficients and claimed the insignificance of the individual coefficients is of no surprise and the estimated coefficients cannot be interpreted as elasticities. Instead, the VAR model is rather used for forecasting and testing hypothesis through experiments.

[49] The model was estimated using the statistical software package Gretl and JMulTi.

5.3.6.1 Granger causality

The model contains a considerable number of variables and requires estimation of considerable amount of coefficients. In the VAR models, it is often helpful to test the variables for causality. By doing so, we are applying the concept of Granger causality to each individual equation and trying to interpret the results in the context of the VAR model.

The main idea of Granger causality is to examine whether changes in one variable will have some impact on the changes in other variables and thus this variable helps predict the development of the latter variable at some stage in the future. Since one of the uses of the VAR model is the forecasting of the variables (NPL ratio in our case), the analysis of the causality basically provides the information on how much a variable (or groups of variables) help in prediction of the remaining variables.

Granger causality test is usually constructed as an F-test where the null hypothesis is that the lagged information on a variable x_t does not provide any statistical significant information about a variable y_t.[50] In other words, that x_t does not Granger cause the variable y_t.

Granger causality is a standard tool investigated in most autoregression models, but the results should be used and interpreted with caution. The Granger causality is best investigated and most useful and usually straightforward to interpret and think about in a bivariate setting of the system, where the hypothesis about the causality can be stated easily. Usually, it is hard to find some clear conclusion about the causality when there are more variables involved in the model.

Moreover, Lütkepohl (2005) lists major limitations in the context of Granger causality, which can lead to distortion of the obtained results. Since we usually work with a low-dimensional VAR models, one of the major problems is the potential incompleteness of the model. Another drawback of the Granger causality is the choice of the information set and the choice of sampling period. Lütkepohl (2005) showed that one obtains different results when considering monthly data and when considering quarterly data. Furthermore, he

[50] The model for causality considered may look like $y_t = \sum \alpha_i y_{t-i} + \sum \beta_i x_{t-i} + \varepsilon_t$ and the null hypothesis as $H_0 : \beta_i = 0 \ \forall i$. Hence, causal relationship is inferred when lagged values of the x_t variable have explanatory power in the regression of a variable y_t on lagged values of y_t and x_t.

proved that using seasonally adjusted variables may lead to different results than putting seasonally unadjusted variables in the model. Thus, he concluded that in a complicated model, lack of Granger causal relationships between the variables does not necessarily have to mean, that there doesn't exist a cause-and-effect relationship.

Figure 22: Granger causality in the VAR model

	Dependent variable							
Regressor	**d_npl**	**d_gdp**	**d_EX**	**d_U**	**d_cpi**	**d_eur**	**d_pribor**	**d_L**
d_npl	**0.0027**	0.2246	0.6514	0.9344	0.6739	0.7253	0.1974	**0.0045**
d_gdp	**0.0106**	**0.0002**	0.6737	**0.0163**	0.6251	0.2132	0.4882	0.5742
d_EX	0.4508	**0.0882**	**0.0052**	0.3787	0.8140	**0.0028**	**0.0015**	0.9883
d_U	0.4629	0.7524	0.6348	**0.0001**	**0.0027**	**0.0719**	0.2762	0.1871
d_cpi	0.6431	0.2752	0.5442	**0.0000**	0.3425	0.2346	0.5571	**0.0873**
d_eur	**0.0241**	0.1238	**0.0168**	0.3716	0.9360	0.4147	0.2169	0.4574
d_pribor	0.4360	0.1983	0.5115	0.5614	0.4181	0.5091	**0.0238**	0.6111
d_L	**0.0466**	**0.0391**	0.1164	0.9826	0.8098	0.2065	**0.0334**	**0.0000**
All	**0.0522**	0.7297	0.3330	**0.0765**	**0.0662**	0.5267	0.1550	**0.0227**

Notes: The results presented show the p-values of the corresponding F-test. The null hypothesis is that the beta coefficients are not significantly different from zero. Rejecting the null hypothesis means that the regressor Granger causes the dependent variable. The results are in bold for p-value less or equal 0.1

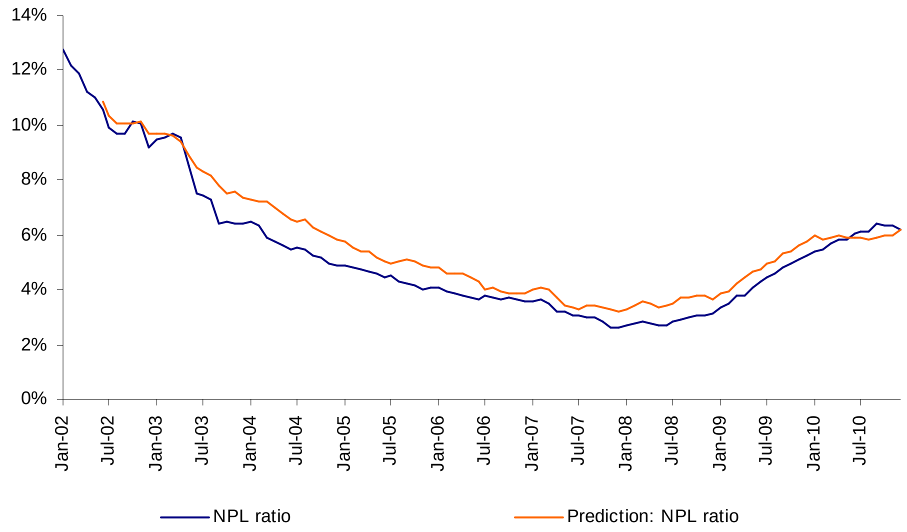
Figure 22 shows the p-values for the F-tests for the VAR model with lag order 4. On the significance level of 10% we can reject the null hypothesis of Granger non-causality in the system for all endogenous variables. Hence, we can conclude that all variables are endogenous and that the Granger causality test revealed some causal relationship between the variables in the model.

5.3.6.2 Forecast of share of non-performing loans in the aggregate loan portfolio

The estimated VAR model was used, and hence also tested for its accuracy, for predicting the NPL ratio over the estimation period (so-called in-sample forecast) and as well as for forecasting the development of the NPL ratio over the following year, i.e. till the end of 2011 (out-of-sample forecast).

The VAR model performed well in terms of the in-sample forecast of the NPL ratio and aggregated loans. One-step-ahead in-sample forecast of the NPL ratio as well as the one-step-ahead in-sample forecast for aggregated loans fit the actual data sample well. The following Figure 23 shows the dynamic in-sample forecast for NPL ratio over the data sample.

Figure 23: Dynamic in-sample forecast of NPL ratio



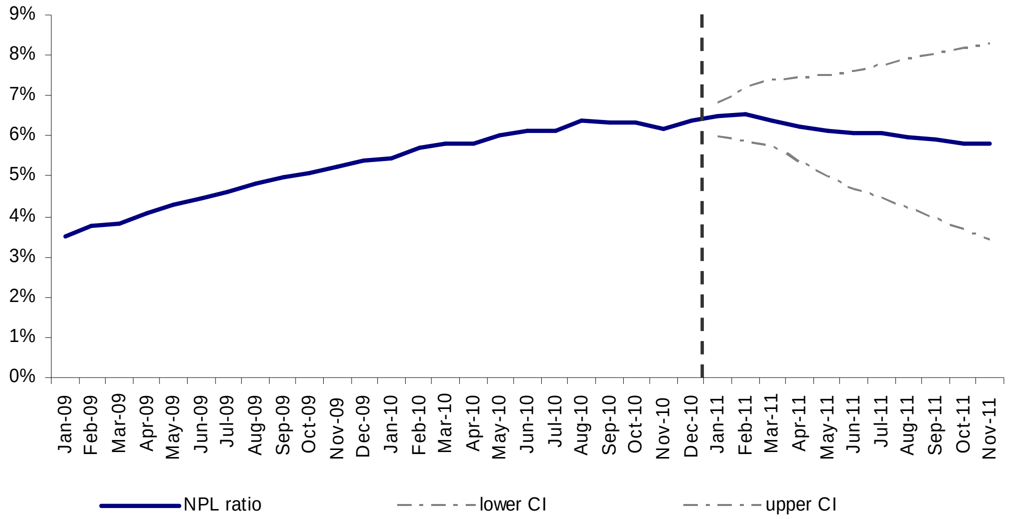
Notes: For detailed information about the underlying forecast of d_npl see Figure 35 in the Appendix. For detailed information about the underlying forecast of d_L see Figure 36 in the Appendix.

However, the performed verification forecast of the NPL ratio for the period 2009 M6 – 2010 M12 didn't match the actual data that greatly.[51] Nevertheless, the actual values did lie within the 95% confidence interval, moreover, the magnitude of the deviations were quite small and the verification forecast appeared to capture the trend of the actual values of the NPL ratio. Therefore, the estimated VAR model was used to forecast the development of the NPL ratio for the upcoming horizon of 12 months.

The likely outlook of the development of the loan portfolio quality is depicted in Figure 24. Under the presumption of the absence of large idiosyncratic shocks or any structural development and changes in the classification rules or interventions, the NPL ratio will stagnate in the first quarter of the year 2011 around 6.5% and subsequently follow a slightly downward trend by approx. 0.7 percentage points. By the end of 2011 the NPL ratio should reach 5.85% of the total loans, which corresponds to approx. CZK 130 billion.

[51] When performing the verification forecast, the VAR model was estimated on the sub-sample of the data sample, i.e. on the period spanning from 2002 M2 – 2009 M6. The out-of-sample forecasted values for the period 2009 M6 – 2010 M12 were compared with the true data. According to the verification forecast, the model seemed to underestimate the true level of the NPL ratio. However, because the verification forecast was carried out on the crisis data, the results are not surprising and have to be interpreted with caution.

Figure 24: Out-of-sample forecast of NPL ratio up to Dec 2011



The lending activity in the Czech banking sector measured as increase in total loans granted should continue to slightly grow up by CZK 56.5 billion over the year 2011. This increase corresponds to 2.6% y-o-y growth in total loans granted, compared to the previous 3.5% y-o-y growth in 2010. Hence, the model predicts a slow down of the lending activity.

5.3.6.3 Impulse response analysis

In this section the usual analysis of the impulse responses gained within the framework of the estimated VAR model will be presented. As mentioned previously, in the framework of VAR models it is hard to make sense of the individual estimated coefficients and their signs, since it cannot be interpreted as elasticities. Nevertheless, as mentioned already in Sims (1980) the best way how to interpret the results of the VAR models is the analysis of the system's responses to a random shock (impulse)[52]. Impulse response functions trace out the impact of one variable on others over the time in the system and hence represent an essential analysis tool when investigating the empirical causal relationships in the system.

The empirical results found by various authors in the selected literature and papers represent an important source of the hypothesis responsiveness investigated in our system. This section follows some of the hypothesis stated in Babouček and Jančar (2005) and tries to find some causal relationships between the loan portfolio quality, and hence consequently on the banking sector credit risk, and several macroeconomic variables.

[52] Impulses are usually one standard deviation shock to error terms.

According to the theoretical literature and empirical findings, the following assumptions with regard to the NPL ratio (as a measure of loan portfolio quality) are expected to be reflected in the impulse response analysis:

1. NPL ratio is exogenous, the NPL ratio is an autoregressive process
2. NPL ratio is pro-cyclical, rising income level improves the ability to service debt
3. higher level of interest rates (reflecting the direct cost of borrowing) should lead to deterioration of the loan portfolio quality
4. high inflation levels should worsen the loan portfolio quality
5. rising unemployment should lead to deterioration of the loan quality portfolio
6. appreciation lowers the competitiveness of domestic economy and therefore leads to acceleration of the NPL growth
7. increase of overall lending activity amplifies the growth of non-performing loans

Besides the investigated causal relations between the loan portfolio quality and the various macroeconomic factors, also other basic empirical hypotheses have been tested. The impulse response function, i.e. the response of a variable to a shock in one standard deviation to error term in other variable, can be found in the Appendix - Figure 40 to Figure 47.

For the purpose of capturing the true dynamic transmission mechanism between the variables in the VAR model, the simulations have to be performed for a reasonably long response periods. In our case, the simulations were performed for 36 periods, which corresponds to development over 3 years. The sufficiently long investigated period was chosen in order to detect regularities in responses of the variables.

The following table represents the results of the basic hypothesis of the relation between NPL ration and macroeconomic variables as source of systemic risk. In addition, the table also contains some other basic hypothesis and empirical findings obtained within the VAR framework.

Figure 25: Basic Hypotheses – results

Hypothesis	Rationale	Supported
Loan Portfolio Quality		
NPL ratio is autoregressive	NPL ratio is exogenous	Yes
Faster GDP growth decreases the NPL ratio growth	Theory of financial sector procyclicality	Yes
Rising export growth improves the loan portfolio quality	Rising export contributes to GDP growth and positively affects export-oriented firms, which in turn results in better repayment condition in the export-oriented sectors and the loan portfolio quality is expected to improve.	No
Rising interest rates accelerates the growth of NPL ratio	Rising interest rates increase direct costs of borrowing and this in turn can lead to worsening of the loan portfolio quality due to the inability of the borrowers to repay their obligations	No
Rising unemployment accelerates the NPL ratio growth	With higher unemployment, households are expected to encounter difficulties when repaying their obligations and the loan portfolio quality worsens.	No
Rising CPI accelerates growth of NPL ratio	Rising inflation makes the macro environment less transparent and creates climate of uncertainty. This raises the information asymmetry and hence leads to adverse selection when granting loans.	No
Appreciation accelerates NPL growth	Appreciation affects the competitiveness of the domestic economy. It causes deceleration in exports and reduction in GDP growth. Depreciation will have a negative effect on loan portfolio quality if borrowers primarily borrowing in foreign currency.	No
Credit expansion increases the growth of NPL ratio	Credit expansion amplifies the likelihood of bad loans	Yes, but not robust
Other hypotheses		
Appreciation decelerates export growth	Movements in exchange rate affect the competitiveness of domestic export industries in global markets. Due to rise of relative domestic prices is harder to sell overseas.	Yes
Appreciation decreases GDP growth	A fall in export demand caused due to the appreciation of domestic currency will reduce real national income relative to potential output.	No
Appreciation decelerates inflation	Negative output gap puts downward pressure on inflation	No
Appreciation accelerates unemployment rate	Reduction in export demand and GDP growth may cause an increase in unemployment, especially in industries more exposed to currency fluctuations.	No
Rising export growth increases GDP growth	Rising export contributes to economic growth in various ways: increasing incentives for technological improvements, pressure of foreign competition, economies to scale, higher productivity leading to efficient management etc.	Yes
Rising GDP growth decreases unemployment	Okun's law	Yes
Faster GDP growth increases inflation	Demand-pull inflation: Aggregate demand for goods and services outpaces supply, causing prices to rise.	No
Faster GDP growth causes an increase in interest rates	Economic growth will raise the demand for money and this causes interest rates to increase	No
Credit expansion supports GDP growth	Credit expansion can lead to an expansion of aggregate monetary demand and expenditure on goods. This can support the economic growth.	Yes
Rising unemployment decreases demand for loans	Negative expectation of households and corporations lead to slow down of the lending activity.	Yes, but not robust

Rising CPI leads to decrease in unemployment	Phillips curve	Yes
Rising CPI causes an increase in interest rates	Inflation erodes the value of money over the duration of the loans, hence lender increase interest rates as response to the increasing inflation.	Yes
Rising interest rates decelerate the lending activity	Higher interest rates makes the loans more costly and hence decelerates the volume of loans	No

Notes: Appreciation is understood as increase in growth of the d_eur variable. Cholesky ordering of the variables used to obtain the impulse response functions: d_eur – d_EX – d_gdp – d_U – d_cpi – d_pribor – d_L – d_npl.

Investigation of the relations affecting the loan quality portfolio is the core topic of this thesis and hence the results to all *a-priori* hypotheses regarding the effect on the loan portfolio quality are presented in the first part of the table.

The results indicate that NPL ratio was autoregressive, which means that a response of the quality of the loan portfolio to a credit risk shock is mainly dominated by the direct negative impact of the loan portfolio quality itself. These findings are in line with results presented in the work of Babouček and Jančar (2005), who found the same direct negative relationship, but in the contradiction to findings of Festić and Romih (2008) for the Czech Republic. In addition, the results don't seem to clearly support the hypothesis that a credit expansion causes deterioration in the loan quality portfolio. Even though, the response of NPL ratio to a shock in lending activity is positive over the first three periods, the response dies out quickly; moreover, the cumulative impulse response function indicates the results are not significant.

On the contrary, the hypothesis that higher income level improves the ability of the borrowers to service their debts was supported by the impulse response analysis. The results show, that an increase in GDP growth fosters an improvement in the loan portfolio quality. The growth of NPL ratio decreases quickly in the consecutive three months and the shock fades away after approx. 20 months. Surprisingly, this result is in contradiction to Babouček and Jančar (2005) who concluded, the rising income does not improve the loan portfolio quality in the Czech Republic. However, they used real money as a proxy of GDP.

In addition, the responses to faster GDP growth seem to support the Okun's law – i.e. negative relationship between economic growth and unemployment, moreover, the response of lending activity seems to support the previous statement. Due to declining unemployment and improving economic conditions, the lending activity seems to increase.

The model, however, failed to detect inflationary pressures, which is in line with findings of Babouček and Jančar (2005). This finding reflects the country-specific feature, since the favourable economic growth in the Czech Republic was accompanied with low inflation level in the past.

Responses to innovations in export confirmed the hypothesis that rising export contributes to economic growth. Increase in export also decreases unemployment, which is in line with the previous statement. The results also showed that increasing export causes the interest rates to rise, however, on the other hand, it also leads to appreciation of the currency. On the contrary to Festić and Romih (2008) who proved that export growth decelerates the NPL ratio growth in the Czech Republic, the results of the model didn't significantly show that rising export contributes to improvement of the loan portfolio quality.

The results failed to support the hypothesis, that rising unemployment accelerates the growth of non-performing loans and therefore contributes to the depletion of the loan portfolio quality. On the contrary, the response of NPL ratio growth to the shock in unemployment rate growth shows the tendency to decrease after 6 months. This result seems to be in line with Festić and Romih (2008) who concluded that rising unemployment decelerates the NPL growth in the Czech Republic. They argued that expected unemployment rate growth decreases the demand for loans and this in turn improves the loan portfolio quality. Indeed, the results indicate that the lending activity immediately declines after the unemployment rate increase, which can explain the later improvement in the loan portfolio quality.

The response of growth of NPL ratio to the shock in consumer price index failed to supports the basic hypothesis that rising inflation accelerates the worsening of loan portfolio quality. The shock to CPI index seems to support the hypothesis, that rising inflation causes increase in interest rates as a consequence of the eroding value of the money. However, the effect on lending activity is not consistent with the previous statement. Moreover, the shock to CPI index failed to support a hypothesis that increasing inflation should have an adverse effect on export (due to lose of the competitive advantage of low wage costs) and hence decrease the economic growth. However, the model supports the basic trade-off hypothesis between inflation and unemployment – the empirical phenomena Phillips curve, i.e. increasing inflation leads to decrease in unemployment.[53]

Also the response of NPL ratio to shock in exchange rate didn't confirm the hypothesis that appreciation accelerates NPL growth and hence leads to worsening of the loan portfolio quality. Also Festić and Romih (2008) didn't find any relationship between appreciation and loan portfolio quality deterioration. However, the results show that appreciation leads to increase in GDP growth, which is in line with findings of Babouček and Jančar (2005). They also concluded that this result corresponds with the country-specific feature, since the rather favourable economic growth (with exception for the financial crisis) was accompanied by appreciation over the investigated period.

The response of NPL ratio growth to an impulse in nominal interest rates didn't confirm the basic hypothesis that increasing cost of borrowing has a direct negative impact on the loan portfolio quality. Festić and Romih (2008) obtained the same result with regard to real interest rates, but Babouček and Jančar (2005) confirmed that increase in real interest rates causes acceleration in NPL ratio. In addition, the results don't seem to confirm the intuitive hypothesis, that rising interest rates cause appreciation and hence reduce exports.

5.3.7 Variance decomposition

Forecast error variance decomposition (FEVD) is another useful tool when interpreting the results obtained through the VAR analysis. FEVD represents decomposition of forecast error variance of one variable into components accounted for by innovations in the remaining variables in the system (Lütkepohl, 2005). In other words, it shows in percentage points how much of the unanticipated changes of one variable are explained by different shocks.

Figure 48 shows the forecast error variance decomposition of the growth of NPL ratio. The results obtained through the analysis of the variance decomposition confirmed the main results. The figure clearly reveals that the biggest effect on the worsening of the loan portfolio quality has the rising growth in NPL ratio itself. The second largest effect is

[53] Babouček and Jančar (2005) obtained exactly opposite results. They concluded, the model supports almost all the basic hypotheses concerning the shock to CPI index- i.e. acceleration in real interest rates accompanied by decreasing demand for loans and worsening of the loan portfolio quality. They also confirmed the decreasing economic activity as a consequence to the inflation shock. However, their model failed to support the Phillips curve. Also Festič and Romih (2008) confirmed that lowering inflation leads to improvement in the loan portfolio quality in the Czech Republic.

attributed to the impact of the development of the economic activity followed by the export growth and CPI index. The effect of the CPI index on the loan portfolio quality is however more delayed. As it is shown in the figure, the effect of the overall lending activity on the development of the NPL ratio is relatively small, since it accounts for only 4% of the NPL ratio growth fluctuation. Quite surprisingly, the same is true also for growth in PRIBOR as a representation of the interest rates.

5.3.8 Residuals analysis

Lütkepohl (2005) stressed the importance to conduct the residual check of the estimated VAR model. Hence, the residual analysis has been performed in order to investigate the robustness of the model. Generally speaking, if the VAR model is specified correctly, the residuals are an *i.i.d*. processes. In order to perform the diagnostic check of the residuals, the autocorrelation test and the residuals' covariance matrix are examined.

Testing for autocorrelation in the residuals was performed using the Ljung-Box Q-test[54] for serial autocorrelation (aka Portmanteau test). The Ljung-Box Q-test checks whether the residuals are white noise.

Figure 26: Results of Ljung-Box Q-test for residuals

Equation	Ljung-Box Q-test	p-value
u_pribor	19.6242	0.0745
u_eur	8.7815	0.7210
u_gdp	11.5504	0.4820
u_EX	11.5165	0.4850
u_U	10.8210	0.5440
u_cpi	29.3247	0.0035
u_npl	9.5280	0.6570
u_L	7.0621	0.8530

Notes: The null hypothesis in the Ljung-Box Q-test is that residuals are white noise. The test was run using lag order 12. Similar results were obtained using lag order of 20.

The Q-test failed to indicate any significant autocorrelation in the residuals with the exception of residuals in regression estimating the inflation. Hence, as mentioned in Babouček and Jančar (2005) the estimated coefficients that suffer from autocorrelation are unbiased, but not the most efficient. As explained in Lütkepohl (2005) a complete lag order structure of the model will cause the residuals to be close to the white noise. Hence, in our case, where the lag order structure of the model is incomplete, the problems with efficiency of the estimated coefficients could have been expected.

[54] For technical details of the Ljung-Box Q-test see for example Lütkepohl (2005), pp. 169 – 171.

Figure 37 to Figure 39 in the Appendix represent the residual analysis of the model. The results for the Jarque-Bera test for normality, which is showed as part of the descriptive statistics, reveal that with the exception of GDP growth, exports, exchange rate and PRIBOR the test rejects the null hypothesis of normality of the residuals at the 5% significance level. At the same time, the descriptive statistics reveals that the violation of the normality is caused by the excess kurtosis (normally distributed sample has excess kurtosis close to zero). This fact indicates that the investigated time series come from a fat-tailed distribution.

5.3.9 Concluding remarks, implication and limitations

The employed VAR model has brought some interesting results with regard to the investigated transmission mechanisms and revealed some causal relationships between the loan portfolio quality and various macroeconomic variables. However, even though it follows methods widely used and established by central banks, there are some issues that need to be addressed.

First and most glaring limitation of the presented VAR model is the limited length of the investigated time series. Namely, the time series of non-performing loans are available only after the year 2002. The problem of short time series leads to the compromise on the lag length structure of the system. As mentioned previously, the model features only incomplete lag structure, more to the point, the data constraint allows consideration of only limited number or regressors. Introducing more variables can help to develop greater understanding how the macro variables interact with each other and how they jointly affect the credit risk indicator. The model can be used in order to draw some conclusions about the risk factors affecting the credit risk and this may lead to possible policy implication on both – the government and possibly also firm level.

In addition, considering only limited number or variables can lead to the omitted variable problem, since omitting important variables leads to distortions in the obtained empirical results. Misspecification of the model due to omitting important variable causes distortion mainly in the impulse response analysis, but its impact on forecasting is small. Hence, the misspecified model can be still used for forecasting purposes. (Lütkepohl, 2005)

The model contains macroeconomic variables that are subject to seasonal fluctuations, such as exports, unemployment rate etc. Some of the variables were available in its seasonally adjusted version. However, the unemployment rate and CPI index enter the model seasonally unadjusted. As pointed out previously, seasonal adjustments may have an effect on the outcome of Granger causality and may also contaminate the forecast error variance decomposition.

The estimated model produced 64 impulse-responses including the autoregressive responses. Some of the responses had the expected sign and confirmed the underlying theory of the hypotheses, however, large share of the responses were not significant or were only weakly significant. More to the point, responses to credit risk shock (acceleration of the growth of non-performing loans) were not significant. Increasing number of observations together with making the macroeconomic variables more specific would provide a more accurate view of the loan portfolio quality in the Czech Republic.

The model contributed to the understanding of macroeconomic factors the Czech banking sector has the greatest exposure and represents a good basis for further stress testing analysis. Formulation of some coherent stress test scenario and introducing the adverse shocks in the model would allow a simulation of the effects under adverse macroeconomic conditions.

6 Conclusion

This thesis is mainly devoted to the empirical part, but pays attention also to methodological issues of stress testing. Stress testing as a tool to gauge the robustness of the financial system has become centre of the attention of central banks as well as risk management departments of commercial banks in recent years. In the beginning, we defined stress testing and specified the stress testing procedure and its general properties. According to the intent of the exercise, stress tests can be divided into stress test run on portfolio basis and stress test conducted on the aggregate level. The theoretical part of the thesis contains a comprehensive comparison of major differences in the definition and aim of stress testing applied to the different levels. Furthermore, it lists reasons for usage of stress test and limitations of applying stress testing procedure on the system-wide basis.

The instability in the system can stem from various factors including the rapidly growing financial innovations, soft loan policy or macroeconomic fluctuations. Macroeconomic changes has been one of the main reason commercial banks experienced losses in the recent crisis and that is why many central banks have aimed their effort to develop a comprehensive model and analytical framework to assess and measure financial stability.

In this thesis, we focused mainly on the assessment of the loan portfolio quality in the Czech banking sector over past nine years, in the time period starting from January 2002 to December 2010. A vector autoregression approach was used to estimate the effect of various macroeconomic variables on the banks' aggregate loan portfolio. Non-performing loans vis-à-vis total loans in the Czech banking sector were employed as a measure of banks' fragility.

The outcome from the vector autoregression model has revealed some interesting causal relationships between the loan portfolio quality and various macroeconomic variables. The results indicated that the biggest effect on the worsening of the loan portfolio quality has the rising growth in NPL ratio itself. In addition, a clear and significant negative relationship was found between GDP growth and the NPL ratio, indicating that an overall improvement in economic activity fosters an improvement in the loan portfolio quality.

However, the results failed to support the remaining *a-priori* hypotheses concerning the relation between NPL ratio and the investigated macroeconomic variables. The model didn't confirm the hypothesis, that rising unemployment accelerates the growth of non-performing loans and therefore contributes to the depletion of the loan portfolio quality. Also, the response of growth of NPL ratio to the shock in consumer price index failed to supports the basic hypothesis that rising inflation accelerates the worsening of loan portfolio quality. More to the point, the response of NPL ratio to shock in exchange rate didn't confirm the hypothesis that appreciation accelerates NPL growth and hence leads to worsening of the loan portfolio quality. Surprising also the hypothesis regarding the interest rates – namely, that rising direct costs of borrowing has a direct negative impact on the quality of the aggregated loans – was not confirmed by the simulation.

Nevertheless, besides the basic hypotheses regarding the loan portfolio quality, numbers of other empirical findings were tested in the simulation. The results of the vector autoregression simulation supported many of the worldwide findings and observed empirical principles.

Besides the investigation of the causal relationships between the macroeconomic variables and the loan portfolio quality, the forecast of the development of the loan portfolio quality in the Czech banking sector was presented. The model predicts slightly slow-down of the overall lending activity over the year 2011. As far as the loan portfolio quality is concerned, the model predicts a graduate decrease in the growth of non-performing loans.

Needless to say, the author is aware of the limitations of the employed vector autoregression model and their impact on the results. Nonetheless, the author believes that this thesis has contributed to the understanding of macroeconomic factors the Czech banking sector has the greatest exposure and that the model represents a good basis for further investigation.

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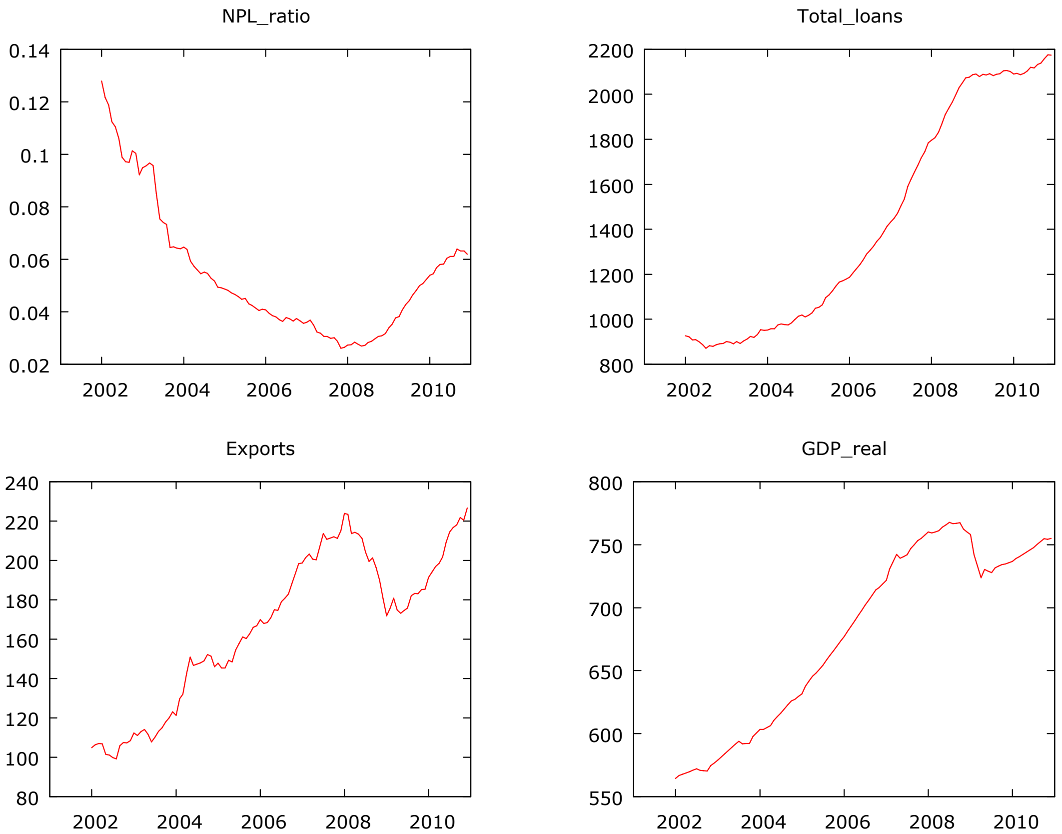
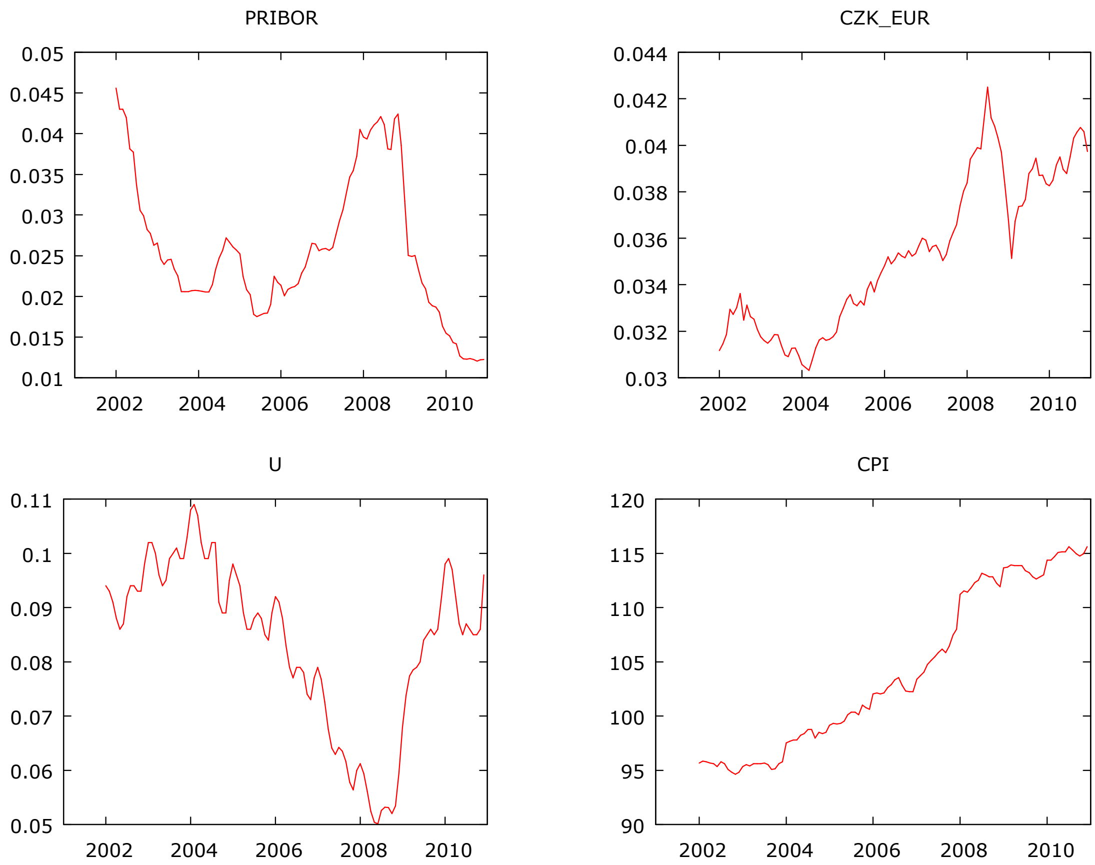
Appendix

Figure 27: Descriptive statistics of original time series

Variable	Obs.	Mean	Median	Min	Max	St. Dev.	Skewness	Ex. Kurtosis	Jarque-Bera	p-value
PRIBOR	108	0.0257	0.0245	0.0120	0.0456	0.0087	0.5864	-0.5115	7.0367	0.0296
CZK_EUR	108	0.0353	0.0352	0.0303	0.0425	0.0033	0.2765	-1.1681	7.3256	0.0257
GDP_real	108	679.6	700.0	564.4	767.7	70.6	-0.3109	-1.4934	11.6623	0.0029
Exports	108	166.4	173.8	99.3	226.6	38.5	-0.2971	-1.1780	7.6500	0.0218
U	108	0.0836	0.0865	0.0501	0.1090	0.0152	-0.6971	-0.4749	9.3970	0.0091
CPI	108	104.2	102.3	94.6	115.6	7.3	0.2665	-1.4869	11.0512	0.0040
NPL_ratio	108	0.0541	0.0476	0.0261	0.1279	0.0248	1.1788	0.5780	24.3360	0.0000
Total_loans	108	1439.0	1297.9	870.7	2175.2	487.8	0.2999	-1.5784	12.6492	0.0018

Figure 28: Plot of original time series (in levels)





Plotted are monthly data for the period of January 2002 to December 2010. *NPL_ratio*, *3M PRIBOR* and *Unemployment rate* are in percentage points. *Export*, *Total_loans* and *GDP_real* are in CZK billion. *CPI* is an index number. Exchange rate is quoted as amount of foreign currency one can get for one CZK (base currency).

Figure 29: ADF test results for original time series

Variable	Lags / Obs.	Test statistics	Standard Error	Critical value	p-value	Stationarity
NPL_ratio	8 / 99	-0.6131	0.0122	-3.13	0.9779	No
Total_loans	5 / 102	-1.9822	0.0088	-3.13	0.6105	No
GDP_real	4 / 103	-1.3890	0.0038	-2.57	0.5892	No
Exports	3 / 104	-0.7999	0.0098	-2.57	0.8187	No
PRIBOR	1 / 106	-1.8590	0.0163	-2.57	0.3522	No
U	5 / 102	-1.5410	0.0160	-2.57	0.5129	No
CPI	0 / 107	0.3411	0.0071	-2.57	0.9794	No
CZK_EUR	1 / 106	-1.0830	0.0165	-1.62	0.7249	No

Notes: In ADF test, the null hypothesis is the presence of unit root in the time series. Null hypothesis is rejected if the t-statistics is smaller than the relevant critical value. Under the null hypothesis the time series has a unit root and hence is non-stationary. When null hypothesis is rejected, the time series is stationary. Optimal number of lags was detected using the Akaike's information criterion. The critical values represent the 10% level of significance. Critical values obtained from Davidson, R. and MacKinnon, J. (1993).

For variables *NPL_ratio* and *Total_loans* the ADF test was based on model with intercept and trend:

$$\Delta y_t = a_0 + a_1 t + \phi\, y_{t-1} + \sum_{i=1}^{p-1} \beta_i \Delta y_{t-i} + u_t$$

ADF tests were based on model with intercept for the remaining variables:

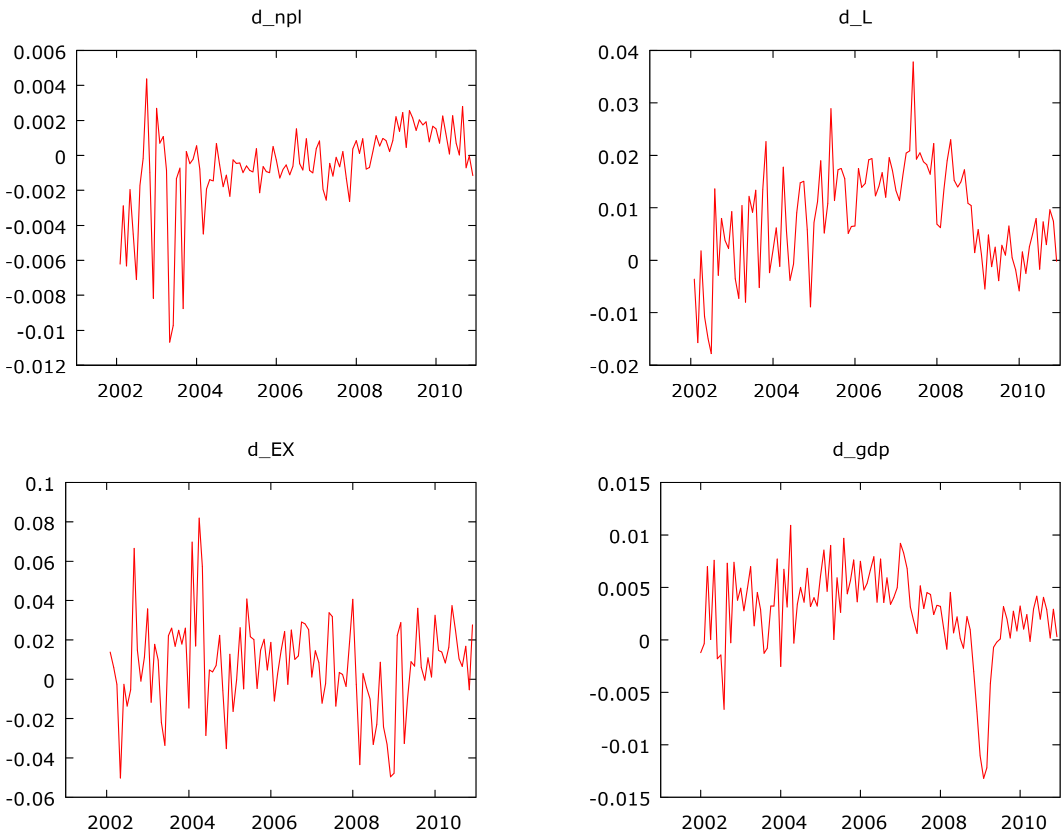
$$\Delta y_t = a_0 + \phi\, y_{t-1} + \sum_{i=1}^{p-1} \beta_i \Delta y_{t-i} + u_t$$

Models are estimated via OLS.

Figure 30: Descriptive statistics of transformed time series

Variable	Obs.	Mean	Median	Min	Max	St. Dev.	Skew.	Ex. Kurt.	Jarque-Bera	p-value
d_pribor	107	-3.12E-04	-9.28E-05	-6.83E-03	3.79E-03	1.64E-03	-1.090	3.625	79.769	0.000
d_eur	107	2.38E-03	4.98E-03	-4.53E-02	4.52E-02	1.52E-02	-0.364	1.082	7.580	0.023
d_gdp	107	2.70E-03	3.20E-03	-1.32E-02	1.09E-02	4.16E-03	-1.250	3.016	71.953	0.000
d_EX	107	7.49E-03	8.64E-03	-5.01E-02	8.20E-02	2.36E-02	0.024	0.975	4.252	0.119
d_U	107	1.87E-05	0.00E+00	-1.10E-02	1.00E-02	3.28E-03	0.234	0.843	4.147	0.126
d_cpi	107	1.78E-03	1.31E-03	-7.84E-03	2.99E-02	5.09E-03	2.171	8.579	412.172	0.000
d_npl	107	-6.16E-04	-4.55E-04	-1.07E-02	4.38E-03	2.50E-03	-1.843	4.507	151.094	0.000
d_L	107	8.06E-03	7.95E-03	-1.78E-02	3.78E-02	9.81E-03	-0.162	0.129	0.543	0.762

Figure 31: Transformed time series



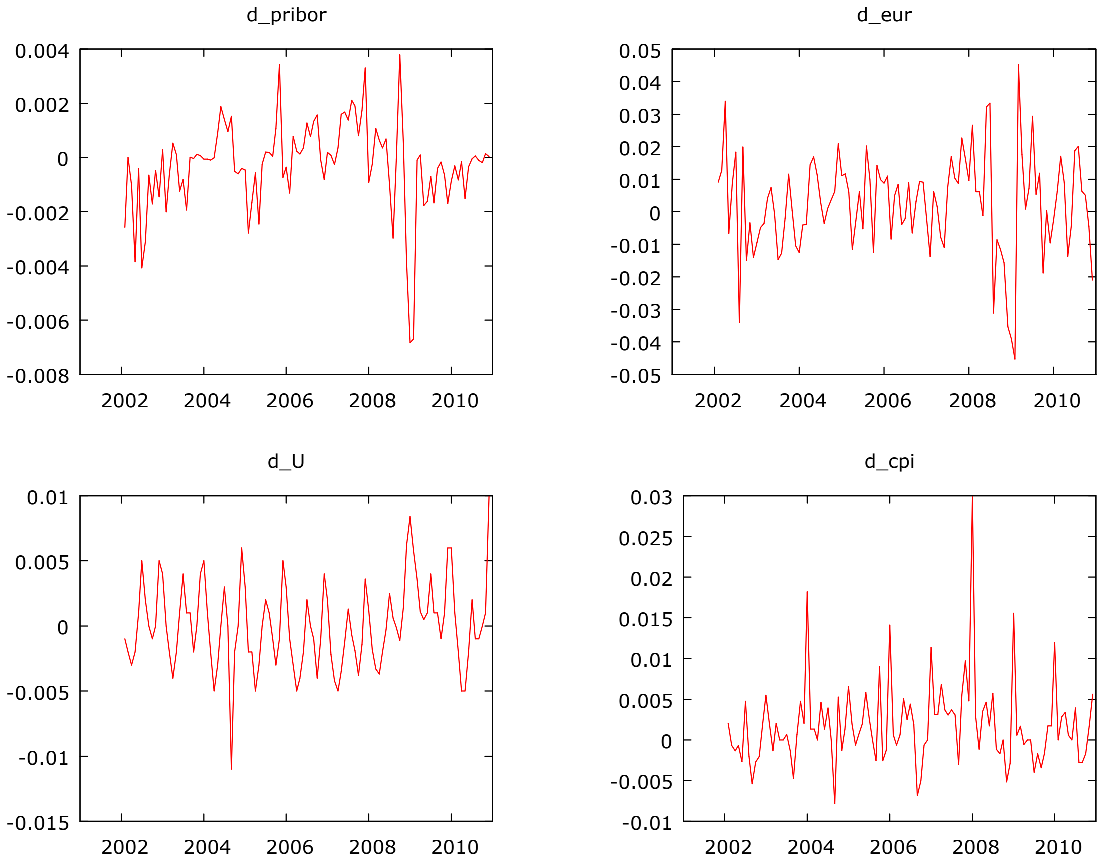


Figure 32: ADF test results for transformed time series

ADF test based on model without intercept and trend: $\Delta y_t = \phi\, y_{t-1} + \sum_{i=1}^{p-1} \beta_i \Delta y_{t-i} + u_t$

Variable	Lags / Obs.	Test statistics	Standard Error	Critical value	p-value	Stationarity
d_npl	4 / 102	-3.0060	0.1289	-1.62	0.0344	Yes
d_L	4 / 102	-1.4084	0.0688	-1.62	0.1483	No?
d_gdp	1 / 105	-2.4183	0.0705	-1.62	0.0156	Yes
d_EX	4 / 102	-2.7400	0.1507	-1.62	0.006	Yes
d_pribor	1 / 105	-5.4068	0.0825	-1.62	5.13E-09	Yes
d_U	10 / 96	-1.7653	0.1883	-1.62	0.0737	Yes
d_cpi	0 / 106	-8.3406	0.0961	-1.62	1.87E-23	Yes
d_eur	0 / 106	-7.9580	0.0955	-1.62	6.54E-20	Yes

Notes: In ADF test, the null hypothesis is the presence of unit root in the time series. Null hypothesis is rejected if the t-statistics is smaller than the relevant critical value. Under the null hypothesis the time series has a unit root and hence is non-stationary. When null hypothesis is rejected, the time series is stationary. Optimal number of lags was detected using the Akaike's information criterion. The critical values represent the 10% level of significance (critical value for 5% and 1% significance level is -1.94 and -2.56, respectively). Critical values obtained from Davidson, R. and MacKinnon, J. (1993).

Figure 33: KPSS test results

Variable	Critical value			Test statistics	Stationarity
	1%	5%	10%		
d_L	0.734	0.465	0.349	0.4839	Yes

Notes: The null hypothesis for the KPSS test is stationarity of the examined time series. Null hypothesis is rejected if the t-statistics is smaller than the relevant critical value.

Figure 34: Software output of the VAR model

VAR system, lag order 4
OLS estimates, observations 2002:06-2010:12 (T = 103)
(Std. Dev.) {p - Value} [t - Value]

Lagged endogenous term:

		d_npl	d_gdp	d_EX	d_L	d_U	d_cpi	d_eur	d_pribor
d_npl	(t-1)	**0.245****	**-0.267***	-1.505	-0.519	-0.009	0.189	-0.736	-0.081
	|	(0.112)	(0.152)	(1.143)	(0.365)	(0.114)	(0.260)	(0.738)	(0.066)
	|	{0.028}	{0.080}	{0.188}	{0.156}	{0.937}	{0.467}	{0.318}	{0.219}
	|	[2.192]	[-1.752]	[-1.317]	[-1.419]	[-0.080]	[0.727]	[-0.998]	[-1.230]
d_gdp	(t-1)	-0.039	**0.324****	0.447	-0.137	-0.026	0.098	-0.024	-0.039
	|	(0.097)	(0.132)	(0.993)	(0.318)	(0.099)	(0.226)	(0.641)	(0.057)
	|	{0.688}	{0.014}	{0.652}	{0.667}	{0.789}	{0.665}	{0.970}	{0.494}
	|	[-0.401]	[2.451]	[0.450]	[-0.430]	[-0.267]	[0.434]	[-0.037]	[-0.684]
d_EX	(t-1)	0.011	0.01	**0.302****	-0.009	-0.018	0.008	**0.331*****	0.012
	|	(0.012)	(0.017)	(0.125)	(0.040)	(0.012)	(0.028)	(0.081)	(0.007)
	|	{0.379}	{0.540}	{0.016}	{0.830}	{0.156}	{0.770}	{0.000}	{0.105}
	|	[0.880]	[0.613]	[2.415]	[-0.214]	[-1.419]	[0.293]	[4.102]	[1.623]
d_L	(t-1)	-0.001	**0.135*****	**0.636***	**0.307****	-0.022	0.035	**-0.547****	**0.041***
	|	(0.037)	(0.050)	(0.377)	(0.121)	(0.037)	(0.086)	(0.243)	(0.022)
	|	{0.970}	{0.007}	{0.092}	{0.011}	{0.559}	{0.681}	{0.024}	{0.058}
	|	[-0.038]	[2.699]	[1.687]	[2.546]	[-0.584]	[0.411]	[-2.251]	[1.893]
d_U	(t-1)	0.084	0.178	1.056	-0.486	**0.385*****	**0.672****	**-2.085****	-0.096
	|	(0.132)	(0.179)	(1.345)	(0.430)	(0.134)	(0.306)	(0.868)	(0.077)
	|	{0.524}	{0.322}	{0.432}	{0.258}	{0.004}	{0.028}	{0.016}	{0.212}
	|	[0.637]	[0.991]	[0.785]	[-1.130]	[2.881]	[2.197]	[-2.402]	[-1.249]
d_cpi	(t-1)	-0.025	0.001	0.303	0.053	-0.021	0.016	0.069	0.028
	|	(0.049)	(0.067)	(0.504)	(0.161)	(0.050)	(0.115)	(0.325)	(0.029)
	|	{0.615}	{0.989}	{0.547}	{0.744}	{0.673}	{0.891}	{0.832}	{0.327}
	|	[-0.503]	[0.014]	[0.602]	[0.327]	[-0.422]	[0.137]	[0.212]	[0.980]
d_eur	(t-1)	0.017	-0.022	**-0.727*****	0.093	-0.001	0.034	-0.019	-0.018
	|	(0.021)	(0.028)	(0.210)	(0.067)	(0.021)	(0.048)	(0.135)	(0.012)
	|	{0.408}	{0.427}	{0.001}	{0.167}	{0.946}	{0.481}	{0.890}	{0.139}
	|	[0.828]	[-0.794]	[-3.466]	[1.381]	[-0.068]	[0.705]	[-0.138]	[-1.479]
d_pribor	(t-1)	-0.25	**0.5***	-0.877	-0.568	-0.065	-0.252	0.683	**0.317****
	|	(0.207)	(0.282)	(2.114)	(0.676)	(0.210)	(0.480)	(1.364)	(0.121)
	|	{0.227}	{0.076}	{0.678}	{0.401}	{0.758}	{0.600}	{0.616}	{0.009}
	|	[-1.209]	[1.774]	[-0.415]	[-0.840]	[-0.308]	[-0.524]	[0.501]	[2.613]
d_npl	(t-2)	-0.155	**0.308***	-0.518	-0.59	-0.007	-0.249	0.212	-0.048
	|	(0.114)	(0.155)	(1.167)	(0.373)	(0.116)	(0.265)	(0.753)	(0.067)
	|	{0.176}	{0.048}	{0.657}	{0.114}	{0.951}	{0.348}	{0.778}	{0.477}
	|	[-1.354]	[1.981]	[-0.444]	[-1.581]	[-0.061]	[-0.939]	[0.282]	[-0.712]
d_gdp	(t-2)	**-0.295*****	**0.322****	-0.107	0.195	**-0.243****	0.042	0.327	-0.014
	|	(0.096)	(0.131)	(0.983)	(0.314)	(0.098)	(0.223)	(0.635)	(0.056)
	|	{0.002}	{0.014}	{0.914}	{0.536}	{0.013}	{0.851}	{0.606}	{0.801}
	|	[-3.063]	[2.460]	[-0.108]	[0.619]	[-2.482]	[0.188]	[0.515]	[-0.252]
d_EX	(t-2)	0.001	**0.045****	**0.228***	-0.012	0.007	-0.029	-0.002	**0.021*****
	|	(0.013)	(0.018)	(0.137)	(0.044)	(0.014)	(0.031)	(0.088)	(0.008)
	|	{0.953}	{0.014}	{0.095}	{0.786}	{0.623}	{0.359}	{0.985}	{0.007}
	|	[0.059]	[2.462]	[1.667]	[-0.271]	[0.492]	[-0.917]	[-0.018]	[2.718]

d_L	(t-2)	**0.09****	**-0.095***	**-0.905****	0.173	0.005	0.062	-0.096	0.008
	|	(0.038)	(0.052)	(0.390)	(0.125)	(0.039)	(0.089)	(0.252)	(0.022)
	|	{0.019}	{0.069}	{0.020}	{0.165}	{0.905}	{0.487}	{0.702}	{0.735}
	|	[2.355]	[-1.821]	[-2.320]	[1.389]	[0.119]	[0.695]	[-0.382]	[0.338]
d_U	(t-2)	0.076	0.042	-1.693	0.093	-0.209	-0.151	0.119	-0.059
	|	(0.140)	(0.191)	(1.436)	(0.459)	(0.143)	(0.326)	(0.927)	(0.082)
	|	{0.588}	{0.826}	{0.238}	{0.840}	{0.144}	{0.644}	{0.897}	{0.471}
	|	[0.542]	[0.220]	[-1.179]	[0.202]	[-1.461]	[-0.462]	[0.129]	[-0.721]
d_cpi	(t-2)	0.032	-0.043	-0.326	**-0.271***	-0.004	0.149	0.481	0.017
	|	(0.047)	(0.064)	(0.483)	(0.154)	(0.048)	(0.110)	(0.312)	(0.028)
	|	{0.499}	{0.499}	{0.500}	{0.079}	{0.941}	{0.176}	{0.122}	{0.538}
	|	[0.676]	[-0.676]	[-0.675]	[-1.758]	[-0.074]	[1.354]	[1.545]	[0.615]
d_eur	(t-2)	0.025	**0.065****	0.118	-0.062	**-0.04***	-0.016	**0.273***	0.01
	|	(0.021)	(0.029)	(0.218)	(0.070)	(0.022)	(0.050)	(0.141)	(0.013)
	|	{0.241}	{0.026}	{0.587}	{0.370}	{0.066}	{0.745}	{0.052}	{0.428}
	|	[1.174]	[2.225]	[0.544]	[-0.896]	[-1.837]	[-0.325]	[1.943]	[0.793]
d_pribor	(t-2)	0.112	-0.47	0.239	0.515	0.334	0.69	-2.099	**-0.284****
	|	(0.214)	(0.292)	(2.192)	(0.701)	(0.218)	(0.498)	(1.415)	(0.126)
	|	{0.603}	{0.107}	{0.913}	{0.463}	{0.125}	{0.166}	{0.138}	{0.024}
	|	[0.521]	[-1.610]	[0.109]	[0.734]	[1.533]	[1.385]	[-1.483]	[-2.256]
d_npl	(t-3)	0.144	-0.071	0.038	**1.289*****	-0.083	0.342	-0.341	0.109
	|	(0.117)	(0.159)	(1.196)	(0.382)	(0.119)	(0.272)	(0.772)	(0.069)
	|	{0.220}	{0.654}	{0.975}	{0.001}	{0.486}	{0.208}	{0.658}	{0.114}
	|	[1.227]	[-0.449]	[0.032]	[3.370]	[-0.697]	[1.260]	[-0.442]	[1.582]
d_gdp	(t-3)	-0.059	-0.162	-1.247	-0.088	-0.126	-0.147	**-1.065***	-0.008
	|	(0.089)	(0.122)	(0.912)	(0.292)	(0.091)	(0.207)	(0.589)	(0.052)
	|	{0.512}	{0.182}	{0.172}	{0.763}	{0.164}	{0.479}	{0.071}	{0.879}
	|	[-0.656]	[-1.336]	[-1.367]	[-0.301]	[-1.391]	[-0.708]	[-1.808]	[-0.152]
d_EX	(t-3)	0.02	0.011	**0.253***	-0.015	0.013	0.024	-0.081	0.008
	|	(0.014)	(0.019)	(0.146)	(0.047)	(0.014)	(0.033)	(0.094)	(0.008)
	|	{0.157}	{0.559}	{0.082}	{0.741}	{0.375}	{0.465}	{0.389}	{0.351}
	|	[1.416]	[0.584]	[1.737]	[-0.331]	[0.887]	[0.731]	[-0.861]	[0.932]
d_L	(t-3)	0.05	0.015	-0.061	0.081	0.015	-0.03	0.407	0.011
	|	(0.038)	(0.052)	(0.388)	(0.124)	(0.039)	(0.088)	(0.250)	(0.022)
	|	{0.186}	{0.766}	{0.874}	{0.514}	{0.702}	{0.730}	{0.104}	{0.608}
	|	[1.324]	[0.298]	[-0.158]	[0.653]	[0.382]	[-0.345]	[1.625]	[0.514]
d_U	(t-3)	0.119	0.014	1.736	0.622	**-0.358****	**-0.588***	-0.883	0.094
	|	(0.137)	(0.186)	(1.397)	(0.447)	(0.139)	(0.318)	(0.902)	(0.080)
	|	{0.383}	{0.941}	{0.214}	{0.164}	{0.010}	{0.064}	{0.327}	{0.241}
	|	[0.872]	[0.074]	[1.242]	[1.392]	[-2.579]	[-1.851]	[-0.979]	[1.173]
d_cpi	(t-3)	-0.028	**0.117***	0.704	0.209	**-0.207*****	0.087	0.505	0.029
	|	(0.048)	(0.065)	(0.489)	(0.156)	(0.049)	(0.111)	(0.316)	(0.028)
	|	{0.552}	{0.073}	{0.150}	{0.181}	{0.000}	{0.434}	{0.110}	{0.305}
	|	[-0.595]	[1.794]	[1.438]	[1.338]	[-4.256]	[0.782]	[1.599]	[1.025]
d_eur	(t-3)	-0.011	0.033	0.257	0.079	0.019	0.015	-0.036	0.011
	|	(0.021)	(0.029)	(0.218)	(0.070)	(0.022)	(0.050)	(0.141)	(0.013)
	|	{0.590}	{0.249}	{0.238}	{0.258}	{0.387}	{0.769}	{0.801}	{0.394}
	|	[-0.538]	[1.152]	[1.181]	[1.130]	[0.866]	[0.294]	[-0.253]	[0.852]
d_pribor	(t-3)	0.208	-0.015	-2.273	-0.848	0.03	0.024	1.819	-0.072
	|	(0.212)	(0.289)	(2.170)	(0.694)	(0.216)	(0.493)	(1.401)	(0.125)
	|	{0.328}	{0.958}	{0.295}	{0.222}	{0.890}	{0.961}	{0.194}	{0.564}
	|	[0.978]	[-0.053]	[-1.047]	[-1.222]	[0.138]	[0.048]	[1.298]	[-0.577]
d_npl	(t-4)	**0.243****	-0.025	0.627	-0.571	0.092	-0.279	0.932	-0.085
	|	(0.115)	(0.156)	(1.175)	(0.376)	(0.117)	(0.267)	(0.758)	(0.067)

	|	{0.035}	{0.875}	{0.594}	{0.128}	{0.430}	{0.296}	{0.219}	{0.209}
	|	[2.112]	[-0.157]	[0.534]	[-1.521]	[0.789]	[-1.044]	[1.230]	[-1.257]
d_gdp	(t-4)	**0.138***	0.182	0.709	0.318	0.085	0.251	-0.593	-0.057
	|	(0.082)	(0.112)	(0.841)	(0.269)	(0.084)	(0.191)	(0.543)	(0.048)
	|	{0.093}	{0.104}	{0.399}	{0.237}	{0.310}	{0.190}	{0.274}	{0.239}
	|	[1.679]	[1.627]	[0.843]	[1.182]	[1.015]	[1.312]	[-1.094]	[-1.178]
d_EX	(t-4)	0.005	-0.006	-0.181	0.002	-0.015	-0.017	-0.107	0.011
	|	(0.013)	(0.017)	(0.129)	(0.041)	(0.013)	(0.029)	(0.083)	(0.007)
	|	{0.721}	{0.708}	{0.160}	{0.957}	{0.258}	{0.561}	{0.196}	{0.138}
	|	[0.357]	[-0.374]	[-1.403]	[0.054]	[-1.132]	[-0.581]	[-1.292]	[1.483]
d_L	(t-4)	-0.052	-0.01	-0.032	**0.203***	0.004	0.04	0.045	0.017
	|	(0.036)	(0.048)	(0.363)	(0.116)	(0.036)	(0.083)	(0.234)	(0.021)
	|	{0.146}	{0.835}	{0.931}	{0.081}	{0.906}	{0.627}	{0.848}	{0.407}
	|	[-1.452]	[-0.208]	[-0.087]	[1.744]	[0.118]	[0.486]	[0.192]	[0.830]
d_U	(t-4)	-0.004	-0.012	-1.423	**-0.769***	**0.248****	**0.975*****	-0.874	**-0.134***
	|	(0.119)	(0.161)	(1.211)	(0.387)	(0.120)	(0.275)	(0.782)	(0.070)
	|	{0.976}	{0.940}	{0.240}	{0.047}	{0.040}	{0.000}	{0.264}	{0.053}
	|	[-0.030]	[-0.075]	[-1.175]	[-1.985]	[2.056]	[3.541]	[-1.118]	[-1.931]
d_cpi	(t-4)	-0.059	-0.087	-0.114	**0.325***	**-0.176*****	-0.188	-0.293	0.009
	|	(0.054)	(0.074)	(0.555)	(0.177)	(0.055)	(0.126)	(0.358)	(0.032)
	|	{0.278}	{0.240}	{0.837}	{0.067}	{0.001}	{0.136}	{0.413}	{0.767}
	|	[-1.084]	[-1.175]	[-0.206]	[1.829]	[-3.194]	[-1.490]	[-0.818]	[0.296]
d_eur	(t-4)	**0.057 *****	-0.014	0.015	0.002	0.016	-0.016	-0.059	0.015
	|	(0.020)	(0.027)	(0.203)	(0.065)	(0.020)	(0.046)	(0.131)	(0.012)
	|	{0.004}	{0.604}	{0.941}	{0.970}	{0.427}	{0.723}	{0.652}	{0.192}
	|	[2.891]	[-0.518]	[0.074]	[0.037]	[0.795]	[-0.354]	[-0.450]	[1.304]
d_pribor	(t-4)	-0.244	-0.211	**3.335***	-0.254	-0.024	0.502	0.245	0.012
	|	(0.196)	(0.267)	(2.006)	(0.642)	(0.199)	(0.456)	(1.295)	(0.115)
	|	{0.215}	{0.430}	{0.096}	{0.692}	{0.903}	{0.271}	{0.850}	{0.915}
	|	[-1.241]	[-0.789]	[1.662]	[-0.397]	[-0.122]	[1.101]	[0.189]	[0.106]
CONST	|	-0.0010	0.0000	0.0060	0.0000	**0.002*****	0.0010	0.0050	**-0.001*****
	|	(0.001)	(0.001)	(0.006)	(0.002)	(0.001)	(0.001)	(0.004)	(0.000)
	|	{0.297}	{0.816}	{0.292}	{0.888}	{0.002}	{0.686}	{0.203}	{0.000}
	|	[-1.043]	[-0.233]	[1.055]	[0.141]	[3.076]	[0.405]	[1.273]	[-3.532]
Mean dependent var		-0.0005	0.0027	0.0081	0.0086	0.0001	0.0019	0.0020	-0.0003
Sum sq. resids		0.0003	0.0006	0.0326	0.0033	0.0003	0.0017	0.0136	0.0001
R-squared		0.4711	0.6747	0.4134	0.6321	0.7127	0.3814	0.4119	0.5980
Adjusted R-squared		0.2293	0.5260	0.1453	0.4639	0.5814	0.0986	0.1431	0.4143
F(32, 70)		1.9483	4.5374	1.5419	3.7578	5.4267	1.3487	1.5321	3.2543
P-value(F)		0.0104	0.0000	0.0669	0.0000	0.0000	0.1491	0.0698	0.0000
S.D. dependent var		0.0024	0.0042	0.0233	0.0094	0.0033	0.0052	0.0150	0.0016
S.E. of regression		0.0021	0.0029	0.0216	0.0069	0.0021	0.0049	0.0139	0.0012
Durbin-Watson		2.0269	2.0128	1.7412	2.1433	1.8884	2.1392	1.8151	2.0040
AIC	-62.848								
BIC	-56.095								
HQC	-60.113								

Notes: An asterisk (*) denotes significance at the 10% level. A double asterisk (**) denotes significance at the 5% level and three asterisks (***) denote the significance level at the 1% level.

Figure 35: Forecast of d_npl

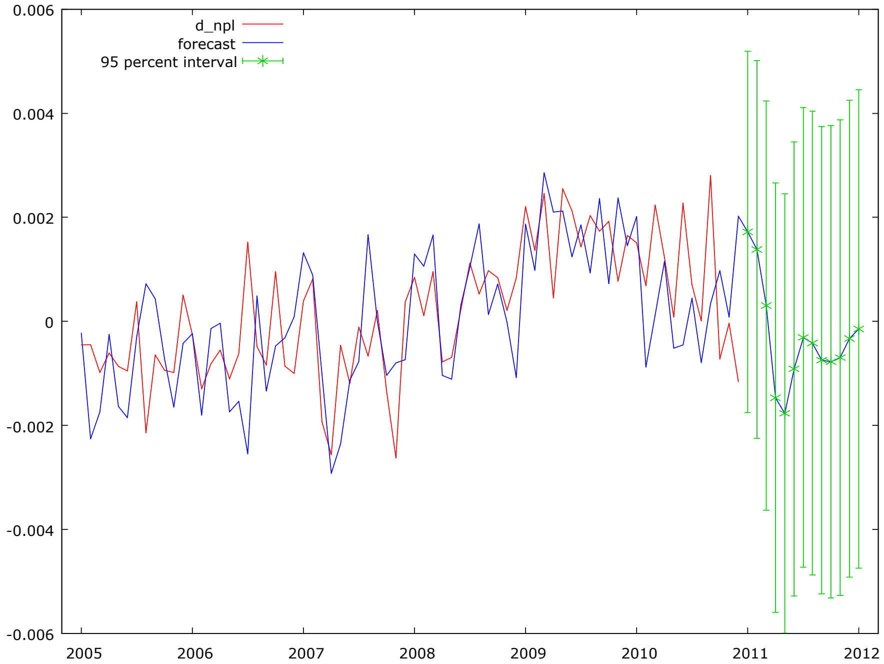
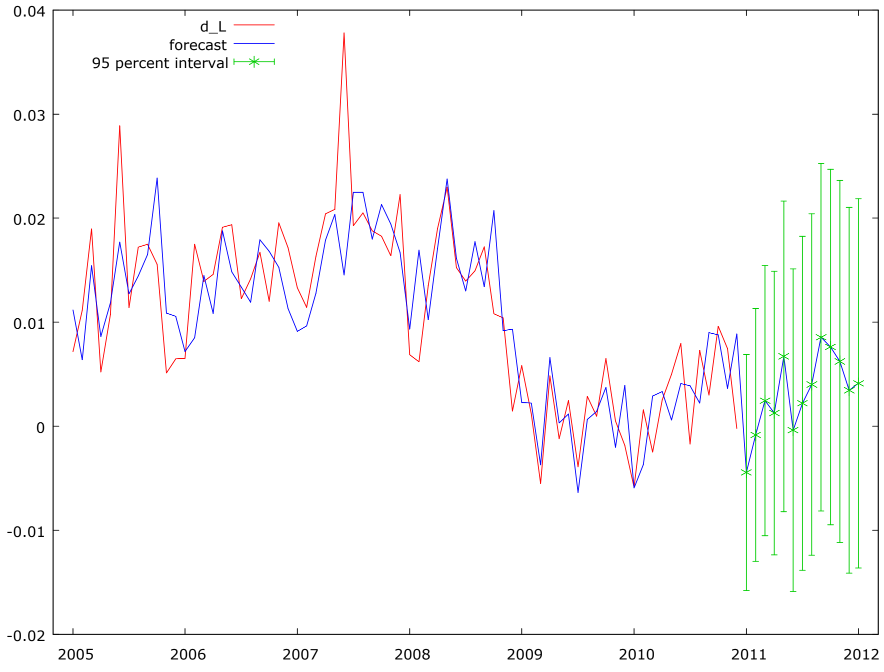


Figure 36: Forecast of d_L



The *h*-step dynamic forecast at time T is obtained based on conditional expectations, assuming the error terms to be independent white noise. The algorithm can be formalized as following:

$$y_{T+h|T} = CD_{T+h} + A_1 y_{T+h-1|T} + \ldots + A_p y_{T+h-p|T}$$

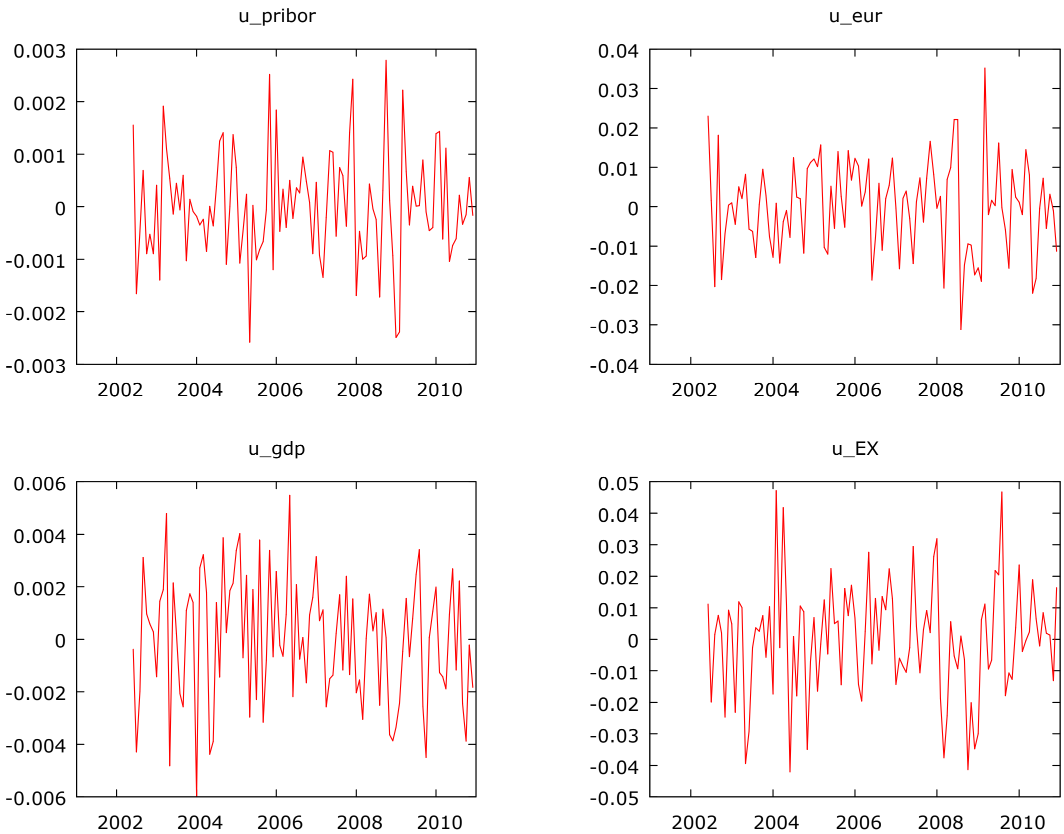
The forecast starts with $y_{T+1|T}$ and is computed recursively for all *h*. The forecasted errors have zero mean and the forecasts are unbiased. The forecasts were obtained through software package gretl and JMulTi.

Figure 37: Descriptive statistics of residuals

Variable	Obs.	Mean	Median	Min	Max	St. Dev.
u_pribor	103	2.32E-19	-6.13E-05	-2.58E-03	2.78E-03	1.03E-03
u_eur	103	5.37E-19	9.93E-04	-3.12E-02	3.51E-02	1.15E-02
u_gdp	103	-6.47E-20	2.21E-04	-5.96E-03	5.48E-03	2.38E-03
u_EX	103	-1.34E-18	2.02E-03	-4.21E-02	4.71E-02	1.79E-02
u_U	103	-2.17E-19	2.03E-04	-7.98E-03	6.71E-03	1.78E-03
u_cpi	103	7.63E-20	-1.57E-04	-8.50E-03	1.89E-02	4.06E-03
u_npl	103	3.78E-20	2.29E-04	-5.79E-03	4.18E-03	1.75E-03
u_L	103	4.41E-19	-1.94E-04	-1.51E-02	2.33E-02	5.72E-03

Variable	Skewness	Ex. kurtosis	Jarque-Bera	p-Value
u_pribor	0.205	0.409	1.4429	0.4860
u_eur	-0.007	0.085	0.0321	0.9841
u_gdp	-0.166	-0.578	1.9070	0.3854
u_EX	-0.059	0.354	0.5999	0.7409
u_U	-0.393	4.011	71.6962	0.0000
u_cpi	1.147	3.771	83.6079	0.0000
u_npl	-0.963	2.123	35.2558	0.0000
u_L	0.283	2.099	20.2813	0.0000

Figure 38: Plot of residuals



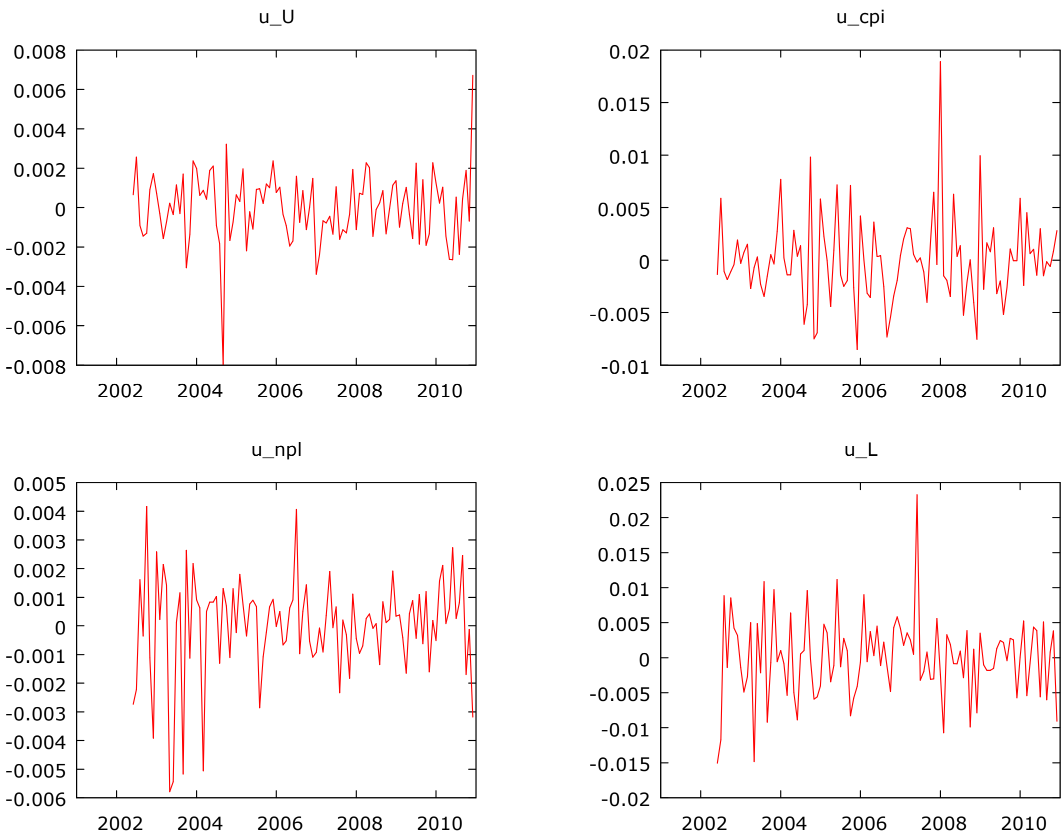


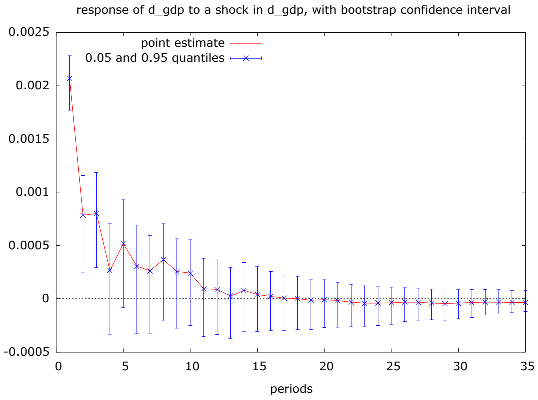
Figure 39: Correlation matrix of residuals

	u_pribor	u_eur	u_gdp	u_EX	u_U	u_cpi	u_npl	u_L
u_pribor	1	0.38	0.2598	0.1167	-0.1468	-0.1687	-0.0111	-0.0557
u_eur		1	0.338	0.1389	0.0085	0.0629	-0.1472	-0.1637
u_gdp			1	0.3949	-0.2915	-0.0894	0.0739	0.2289
u_EX				1	-0.0377	0.1106	0.2206	0.229
u_U					1	0.1858	-0.1869	-0.3378
u_cpi						1	-0.0135	-0.034
u_npl							1	0.2566
u_L								1

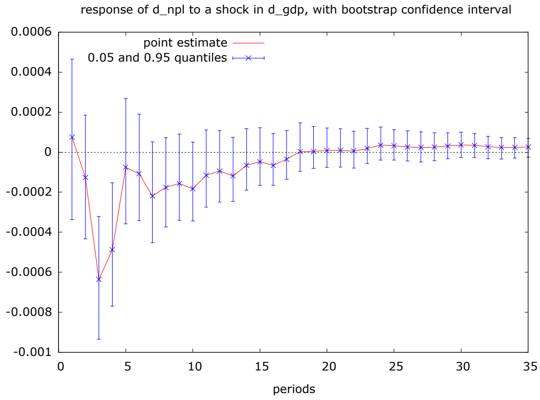
The correlation matrix of the residuals does not show any strong relationship between the individual residuals. The residuals are however correlated between each other.

Figure 40: Impulse to innovations in d_gdp

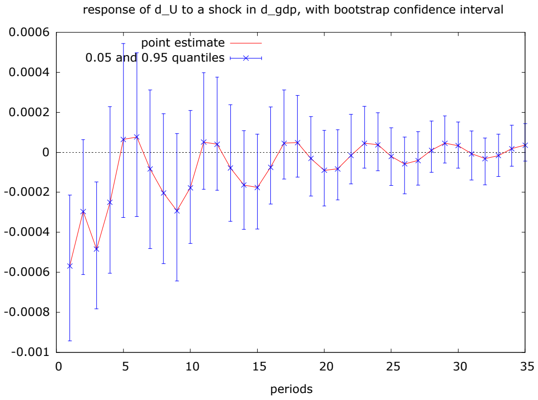
- Autoregressive response



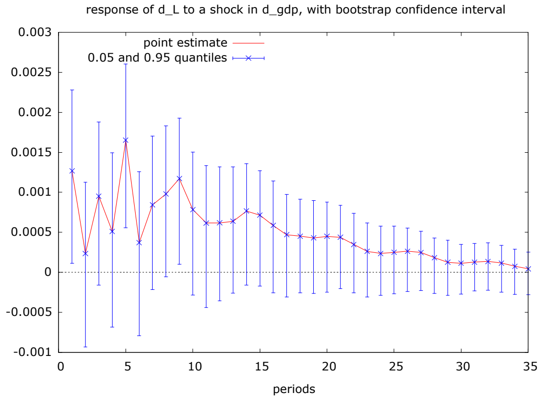
- Response of d_npl



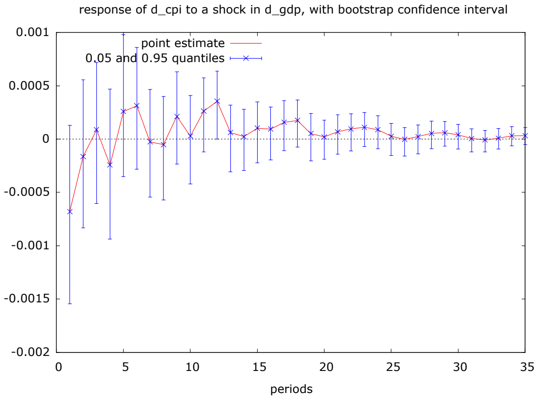
- Response of d_U



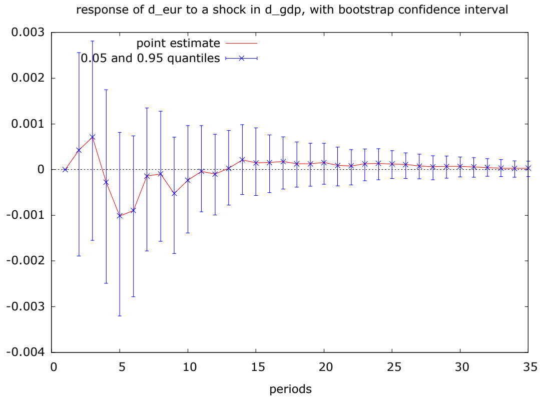
- Response of d_L



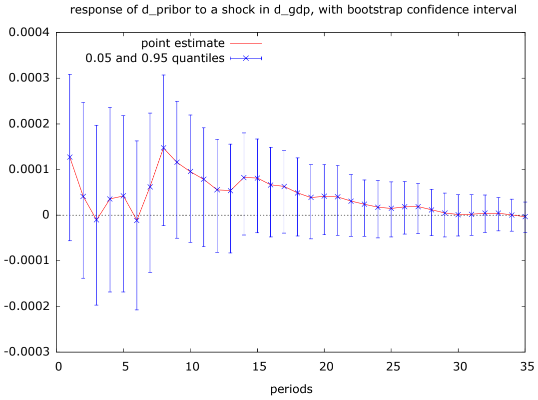
- Response of d_cpi



- Response of d_eur



- Response of d_pribor



- Response of d_EX

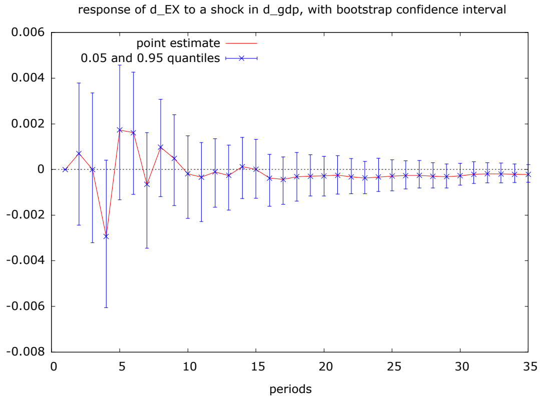
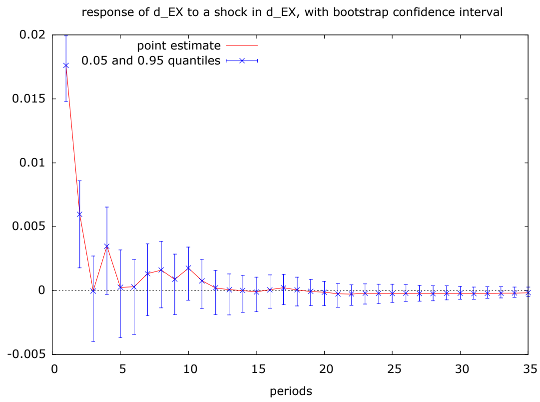
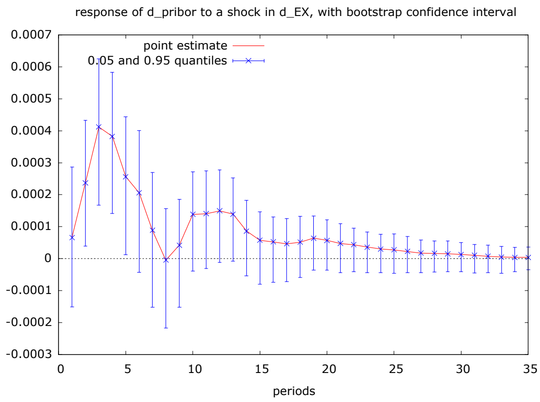


Figure 41: Impulse to innovations of d_EX

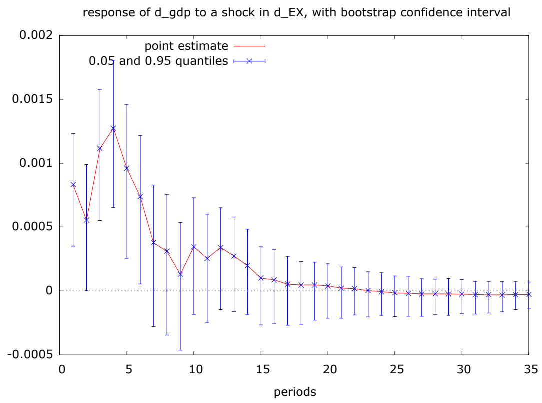
- Autoregressive response



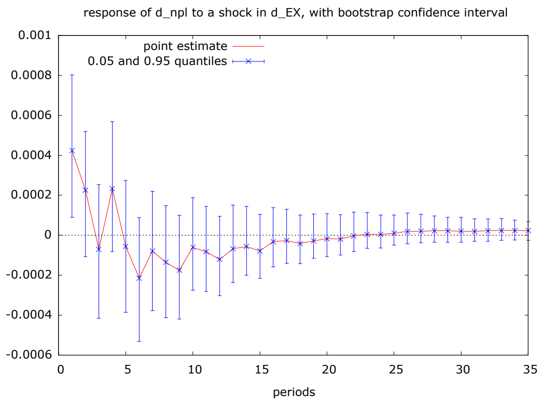
- Response of d_pribor



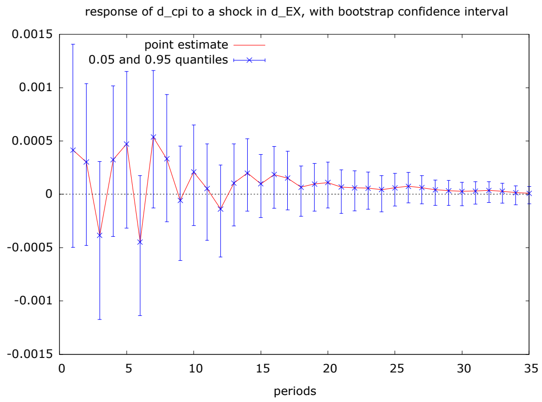
- Response of d_gdp



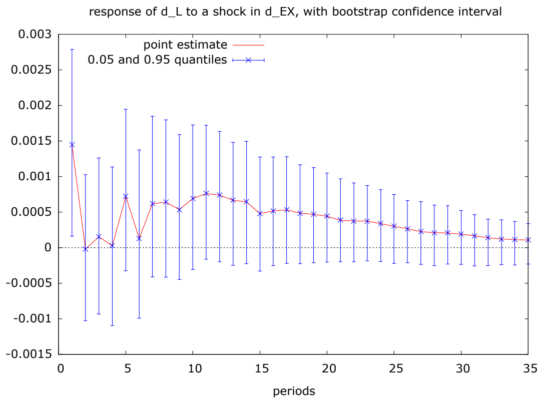
- Response of d_npl



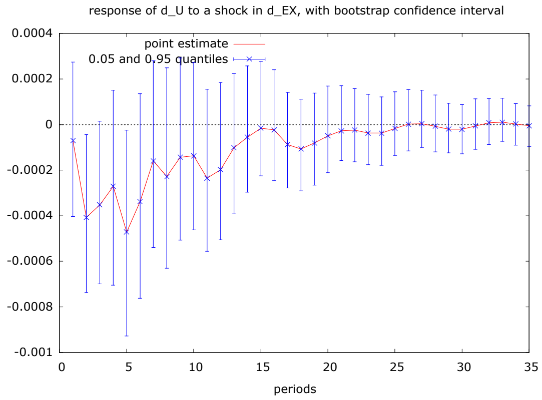
- Response of d_cpi



- Response of d_L



- Response of d_U



- Response of d_eur

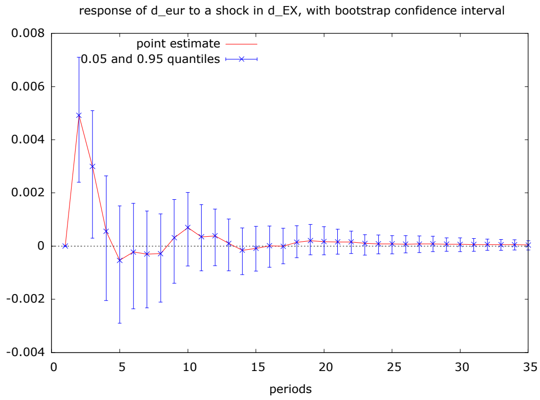
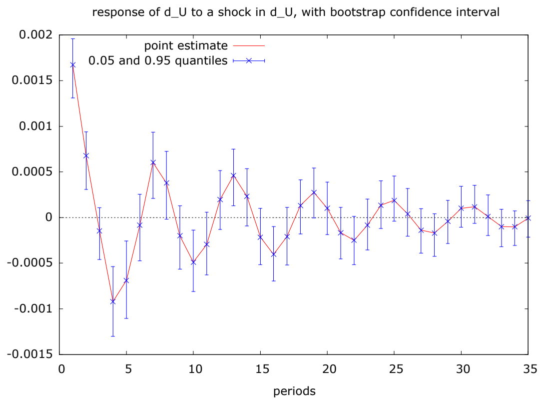
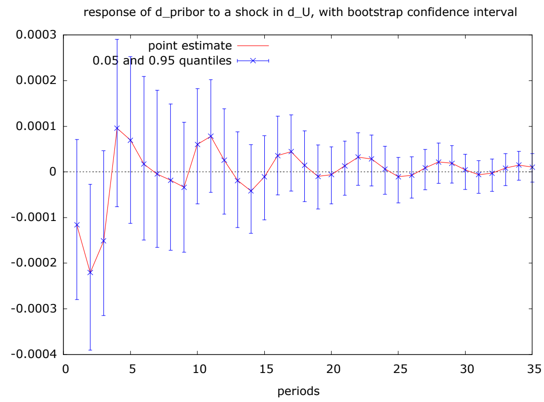


Figure 42: Impulse to innovations of d_U

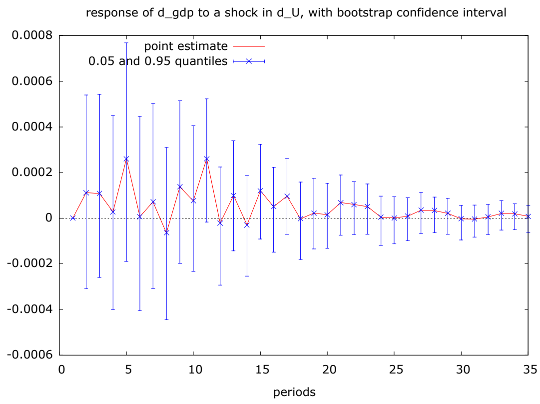
- Autoregressive response



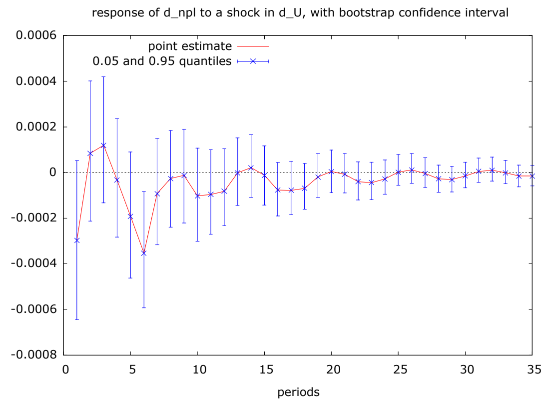
- Response of d_pribor



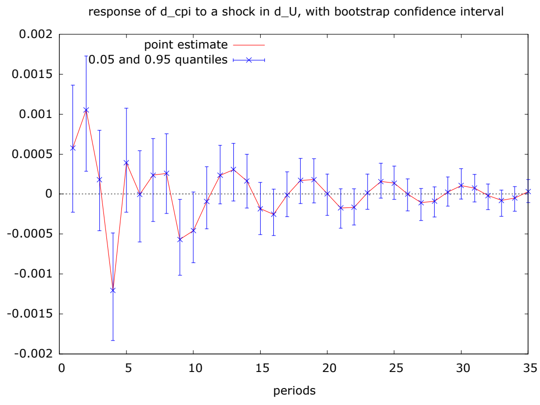
- Response of d_gdp



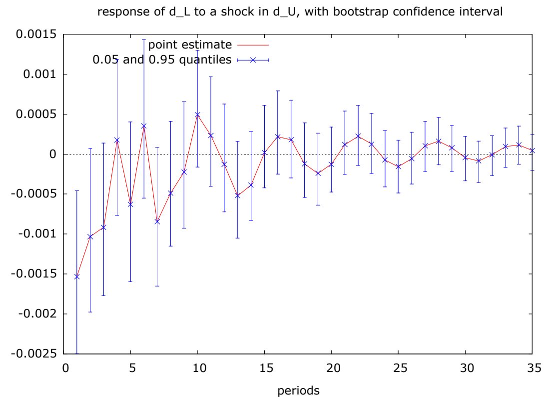
- Response of d_npl



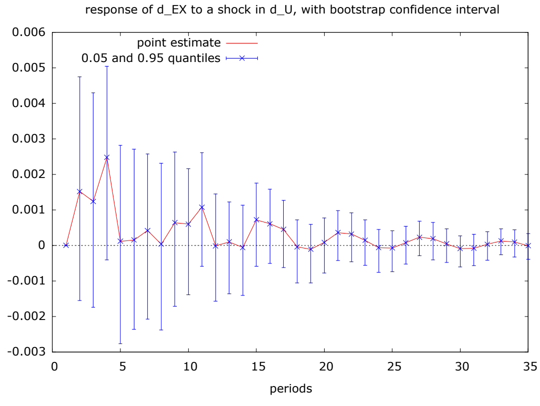
- Response of d_cpi



- Response of d_L



- Response of d_EX



- Response of d_eur

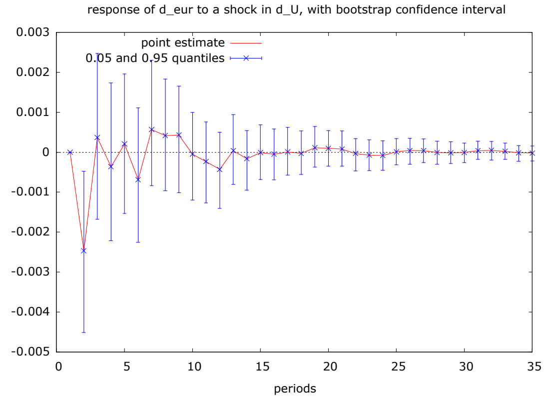
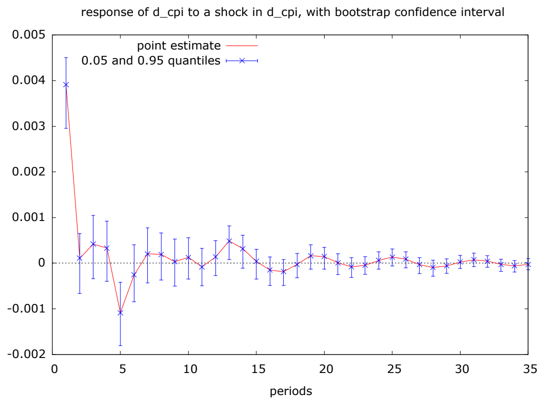
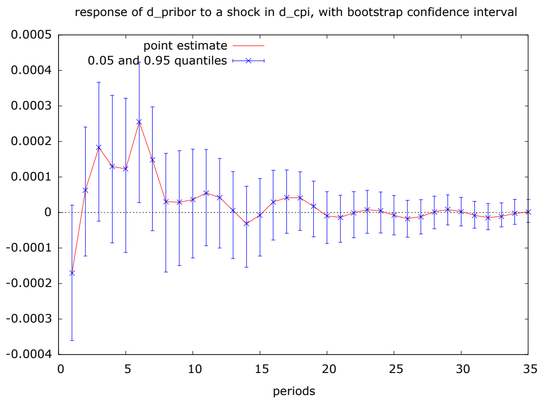


Figure 43: Impulse to innovations of d_cpi

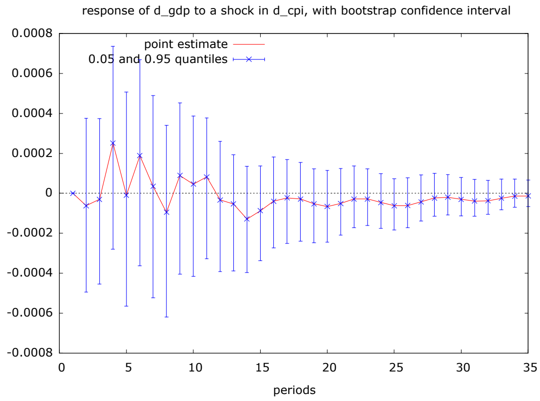
- Autoregressive response



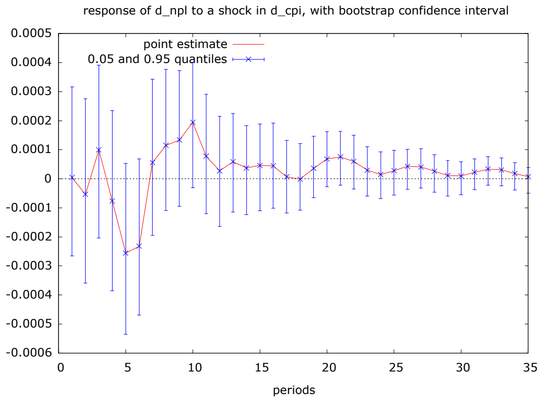
- Response of d_pribor



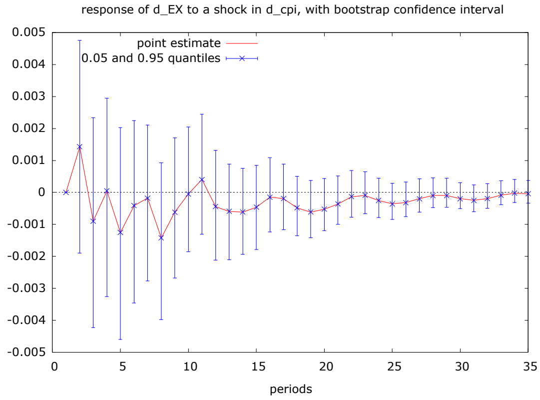
- Response of d_gdp



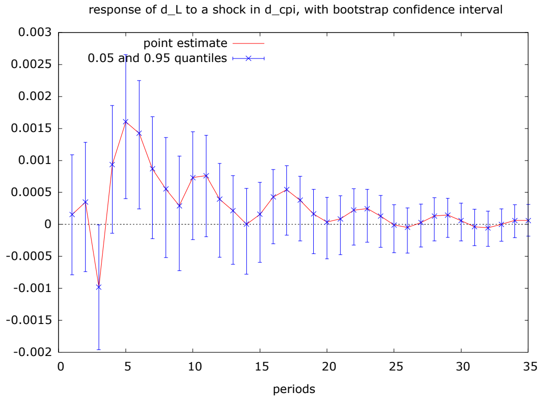
- Response of d_npl



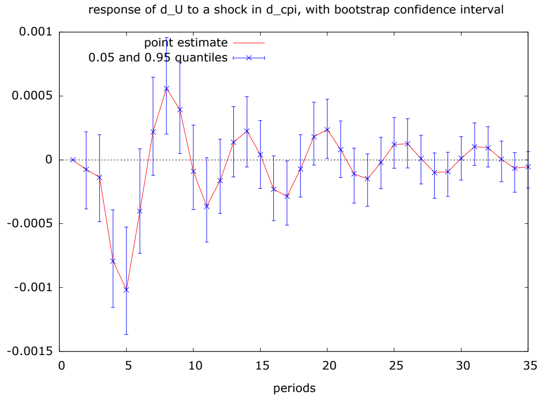
- Response of d_EX



- Response of d_L



- Response of d_U



- Response of d_eur

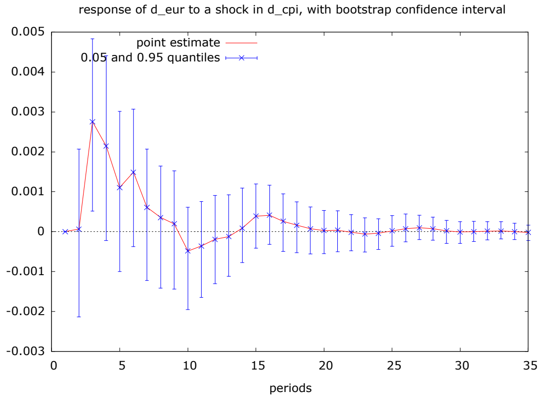
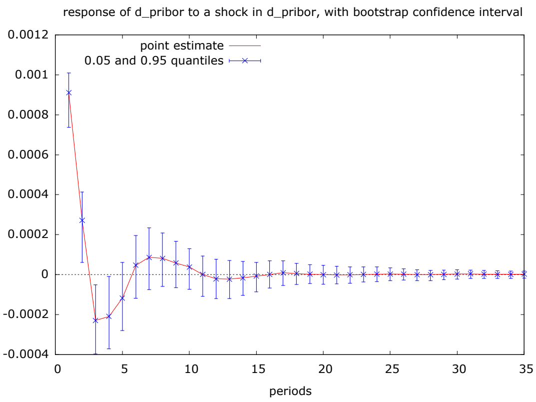
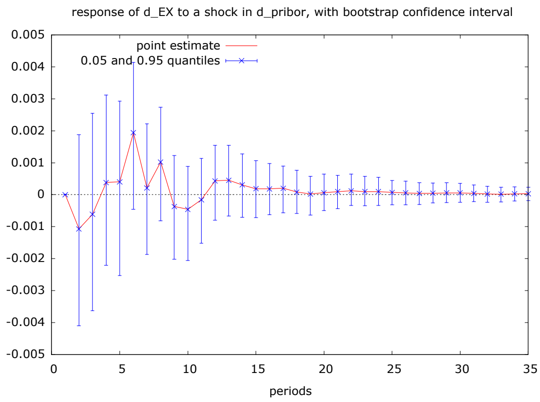


Figure 44: Impulse to innovations of d_pribor

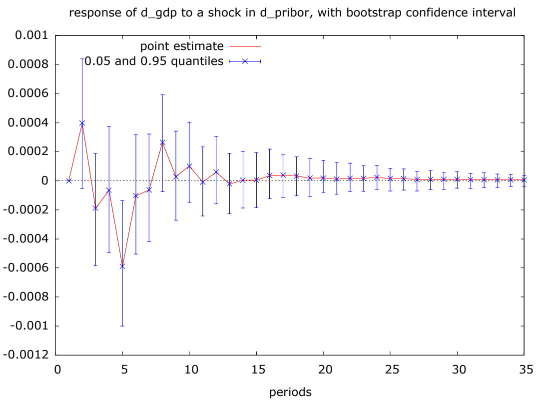
- Autoregressive response



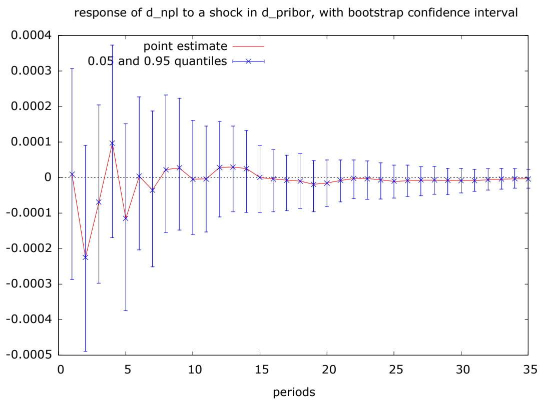
- Response of d_EX



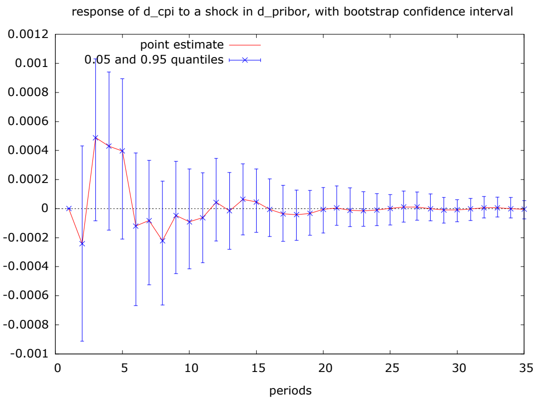
- Response of d_gdp



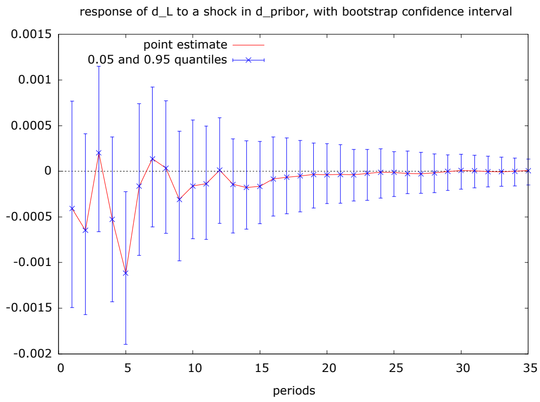
- Response of d_npl



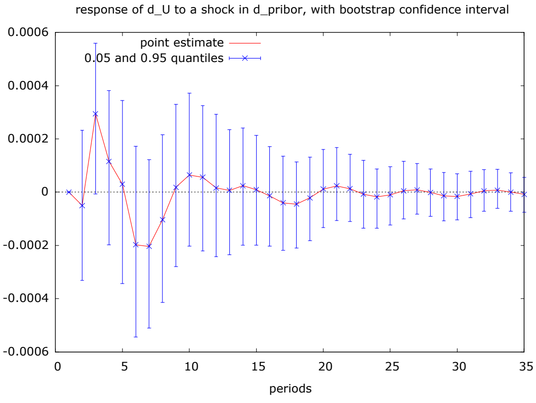
- Response of d_cpi



- Response of d_L



- Response of d_U



- Response of d_eur

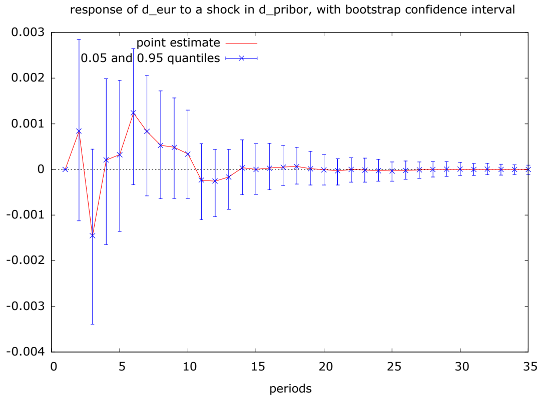
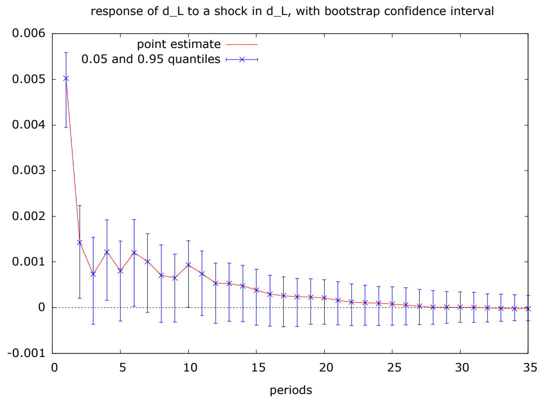
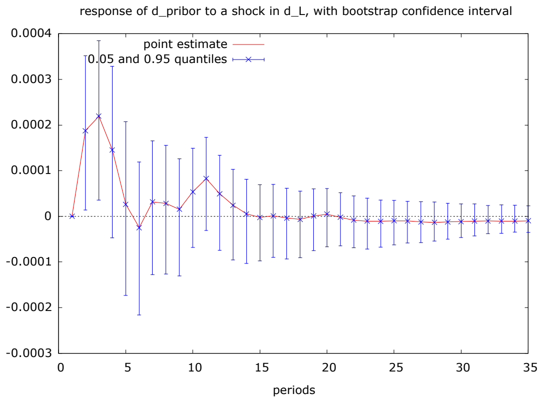


Figure 45: Impulse to innovations of d_L

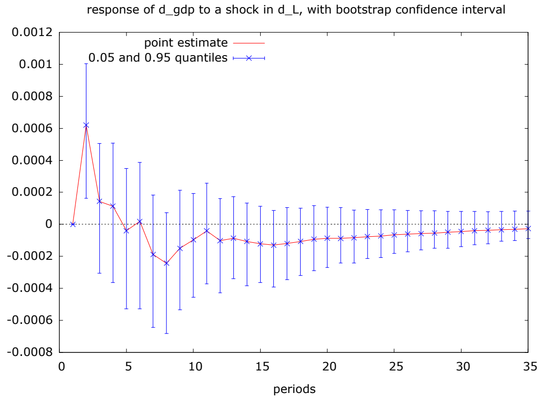
- Autoregressive response



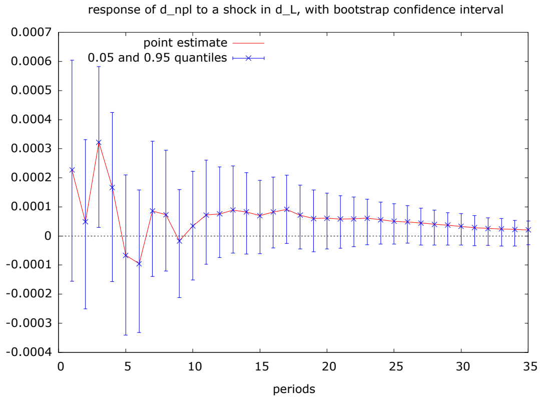
- Response of d_pribor



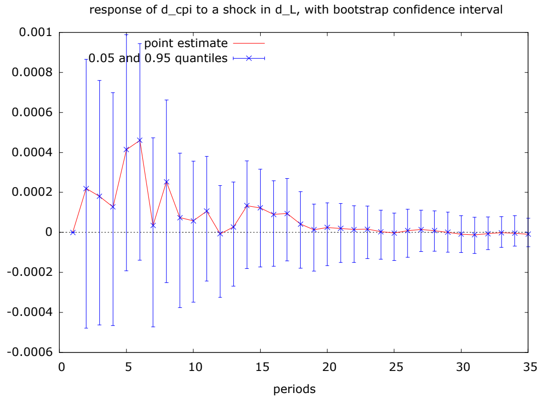
- Response to d_gdp



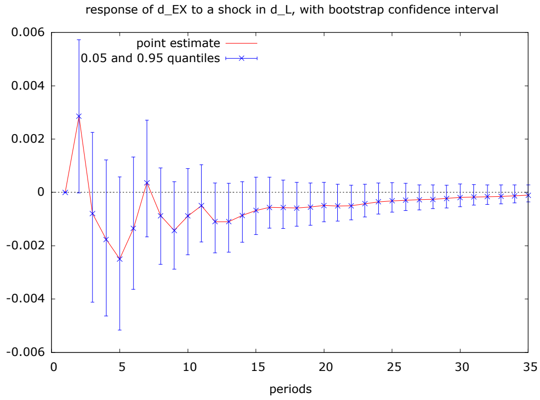
- Response of d_npl



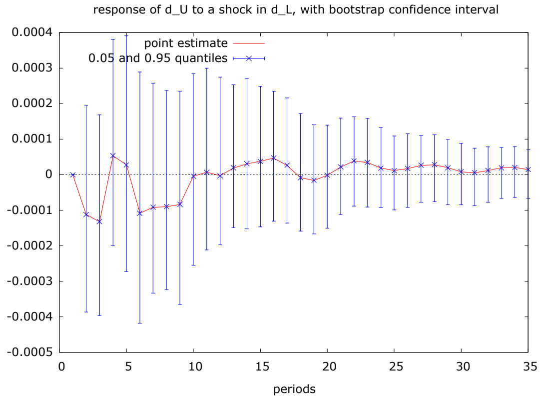
- Response of d_cpi



- Response of d_EX



- Response of d_U



- Response of d_eur

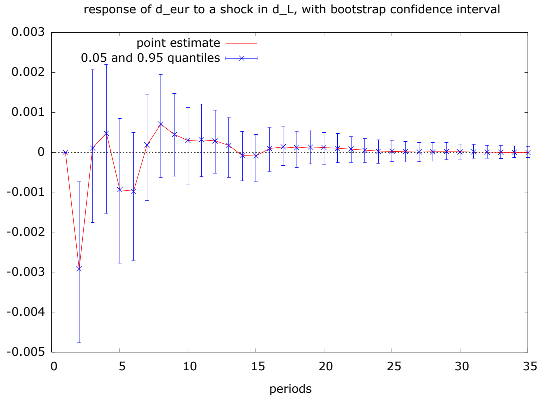
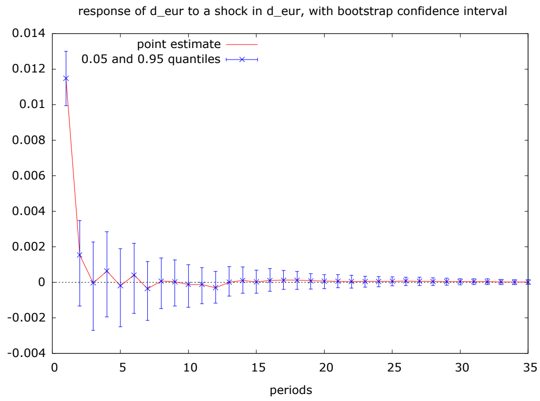
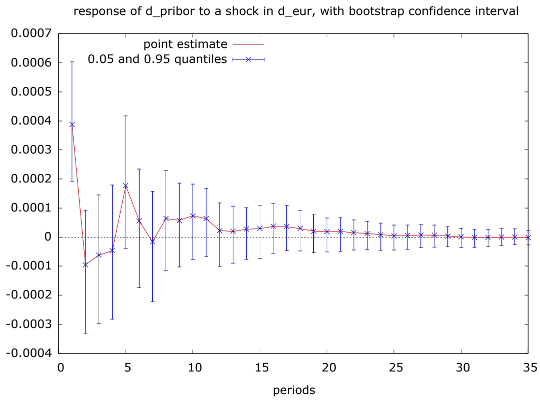


Figure 46: Impulse to innovations of d_eur

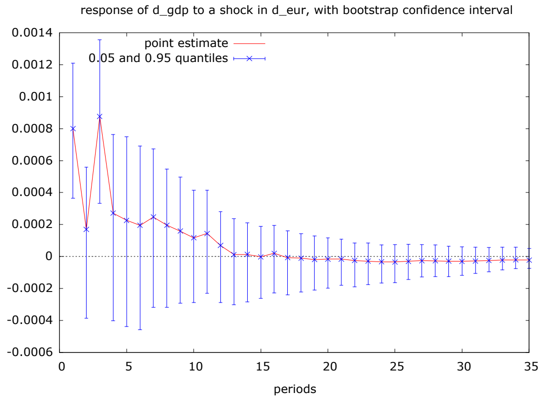
- Autoregressive response



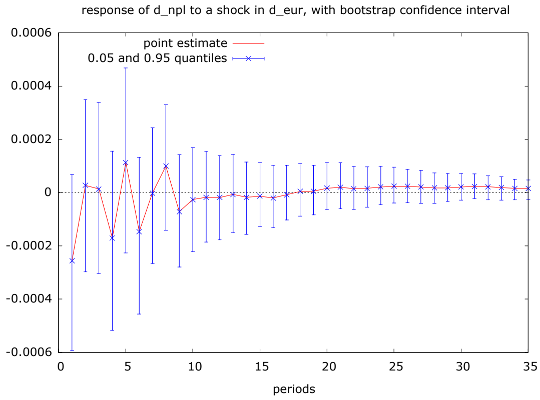
- Response of d_pribor



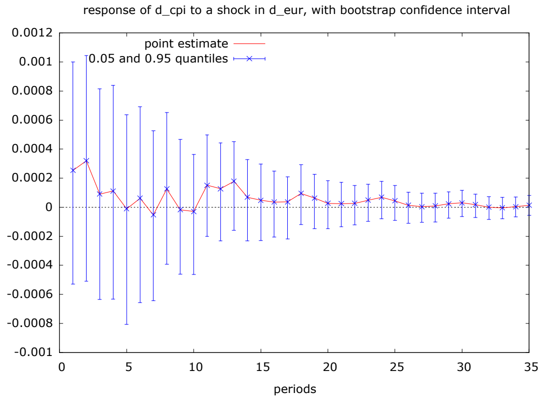
- Response of d_gdp



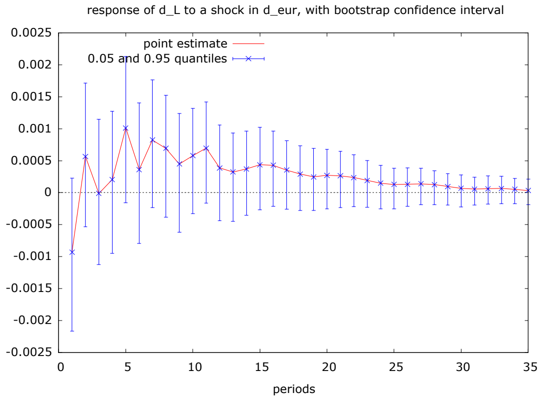
- Response of d_npl



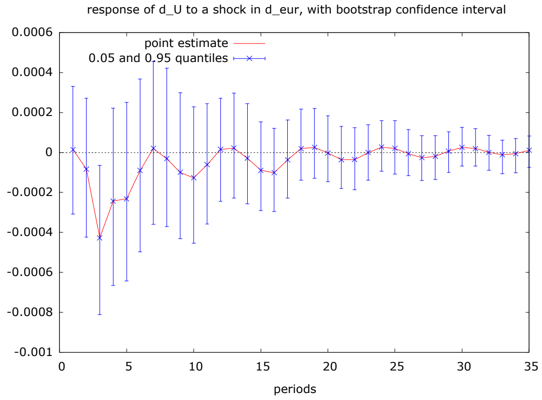
- Response of d_cpi



- Response of d_L



- Response of d_U



- Response of d_EX

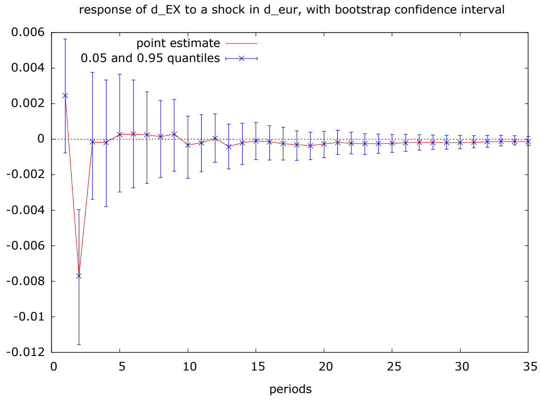
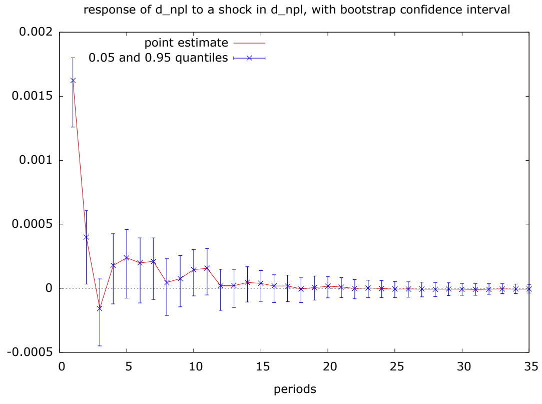
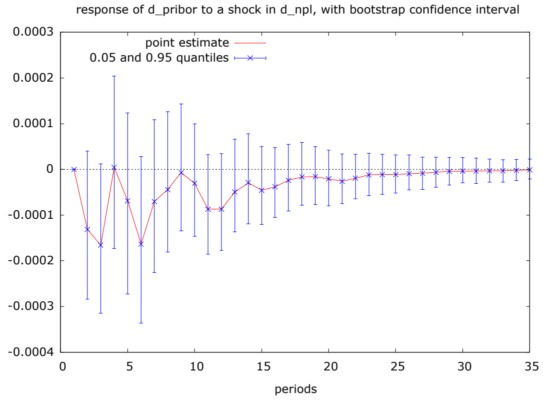


Figure 47: Impulse to innovations of d_npl

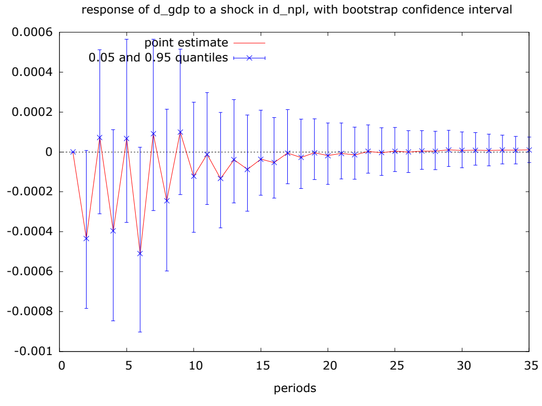
- Autoregressive response



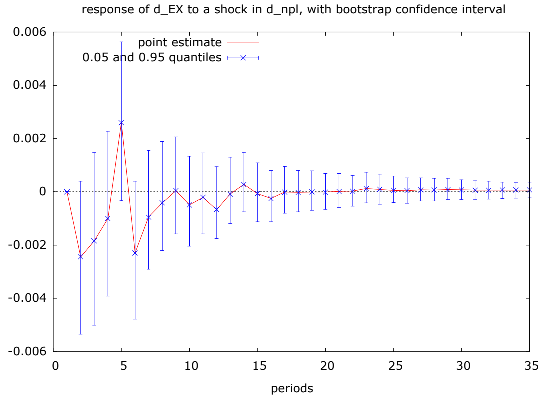
- Response of d_pribor



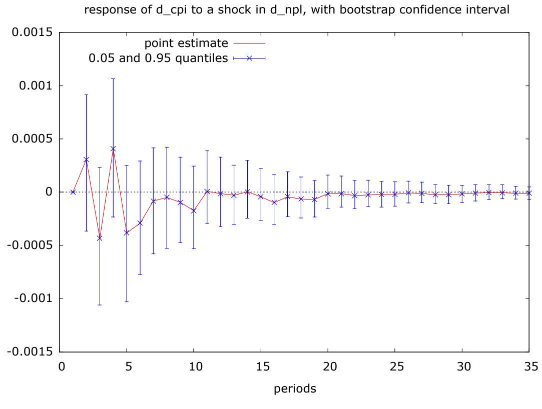
- Response of d_gdp



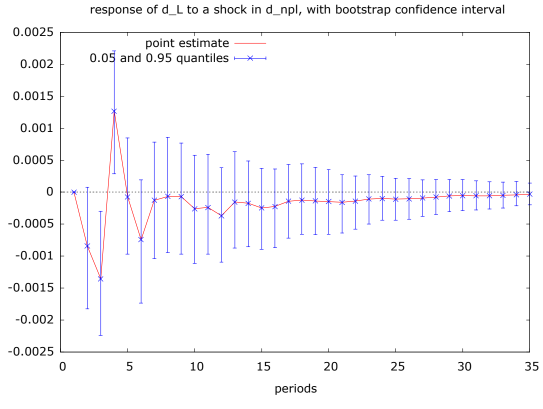
- Response of d_EX



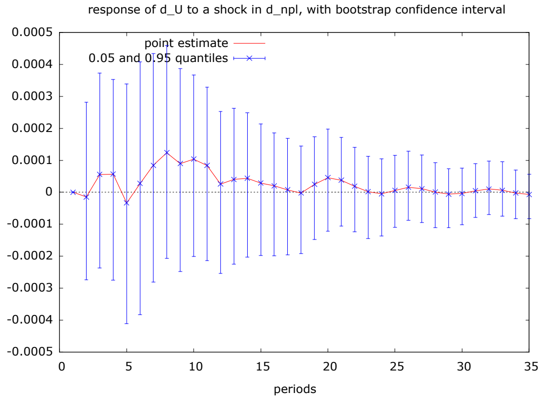
- Response of d_cpi



- Response of d_L



- Response of d_U



- Response of d_eur

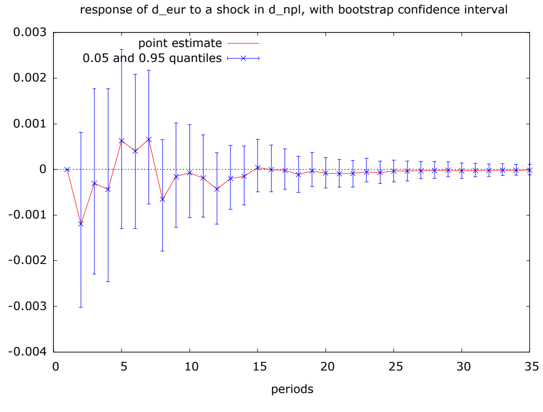
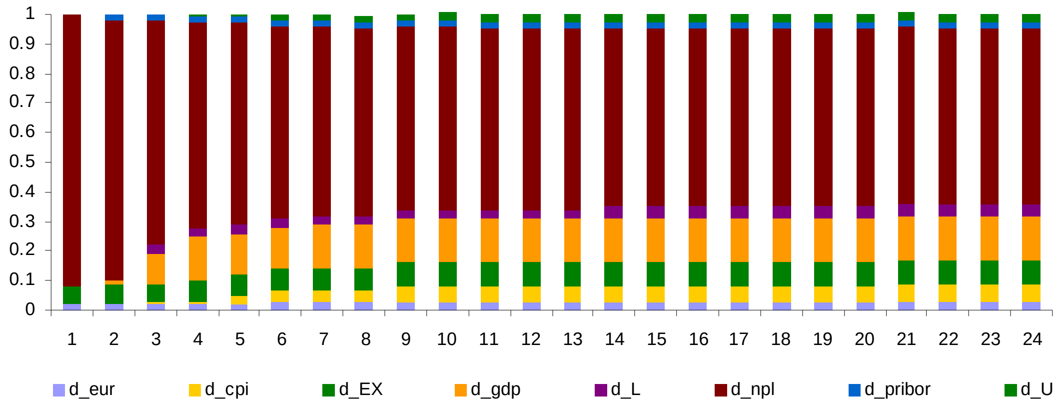


Figure 48: Variance decomposition of d_npl

forecast horizon	d_eur	d_cpi	d_EX	d_gdp	d_L	d_npl	d_pribor	d_U
1	0.02	0	0.06	0	0	0.92	0	0
2	0.02	0	0.07	0.01	0	0.88	0.02	0.01
3	0.02	0.01	0.06	0.1	0.03	0.76	0.02	0.01
4	0.02	0.01	0.07	0.15	0.03	0.69	0.02	0.01
5	0.02	0.03	0.07	0.14	0.03	0.68	0.02	0.01
6	0.03	0.04	0.07	0.14	0.03	0.65	0.02	0.02
7	0.03	0.04	0.07	0.15	0.03	0.64	0.02	0.02
8	0.03	0.04	0.07	0.15	0.03	0.63	0.02	0.02
9	0.03	0.05	0.08	0.15	0.03	0.62	0.02	0.02
10	0.03	0.05	0.08	0.15	0.03	0.62	0.02	0.03
11	0.03	0.05	0.08	0.15	0.03	0.61	0.02	0.03
12	0.03	0.05	0.08	0.15	0.03	0.61	0.02	0.03
13	0.03	0.05	0.08	0.15	0.03	0.61	0.02	0.03
14	0.03	0.05	0.08	0.15	0.04	0.6	0.02	0.03
15	0.03	0.05	0.08	0.15	0.04	0.6	0.02	0.03
16	0.03	0.05	0.08	0.15	0.04	0.6	0.02	0.03
17	0.03	0.05	0.08	0.15	0.04	0.6	0.02	0.03
18	0.03	0.05	0.08	0.15	0.04	0.6	0.02	0.03
19	0.03	0.05	0.08	0.15	0.04	0.6	0.02	0.03
20	0.03	0.05	0.08	0.15	0.04	0.6	0.02	0.03
21	0.03	0.06	0.08	0.15	0.04	0.6	0.02	0.03
22	0.03	0.06	0.08	0.15	0.04	0.59	0.02	0.03
23	0.03	0.06	0.08	0.15	0.04	0.59	0.02	0.03
24	0.03	0.06	0.08	0.15	0.04	0.59	0.02	0.03



Notes: Listing of the forecast error variance decompositions for the remaining variables were omitted due to space reasons.