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

Tatjana Vukelić

Stress Testing of the Banking Sector in Emerging Markets: A Case of Selected Balkan Countries

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Author: **Mgr. Tatjana Vukelić**

Supervisor: **PhDr. Ing. Petr Jakubík, Ph.D.**

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Declaration of Authorship

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Abstract

Stress testing is a macro–prudential analytical method of assessing financial system's resilience to adverse events. This thesis describes the methodology of stress tests and illustrates stress testing for credit and market risks on real bank–by–bank data in two Balkan countries: Croatia and Serbia. Credit risk is captured by macroeconomic credit risk models that estimate default rates of corporate and household sectors. Setting–up the framework for countries that were not much covered in former studies and that face limited availability of data has been the main challenge of the thesis. The outcome can help to reveal possible risks to financial stability. The methods described in the thesis can be further developed and applied to emerging markets that suffer from similar data limitations.

JEL Classification:	E37, G21, G28
Keywords:	banking, credit risk, default rate, macro stress testing, market risk

Author's e–mail:	tatjana.vukelic@seznam.cz
Supervisor's e–mail:	petrjakubik@seznam.cz

Abstrakt

Zátěžové testování je metoda makroekonomické analýzy, která hodnotí odolnost finančního systému proti nepříznivým událostem. Tato práce popisuje metodiku zátěžových testů a ilustruje zátěžové testování pro úvěrové a tržní riziko na skutečných datech jednotlivých bank ve dvou balkánských zemích: Chorvatsku a Srbsku. Úvěrové riziko je vyjádřené pomocí makroekonomického modelu kreditního rizika, který odhaduje míry defaultu pro podnikový sektor a sektor domácností. Hlavním úkolem práce je sestavení rámce zátěžového testování pro země, které nebyly příliš uvažovány v dřívějších studiích a pro které jsou data dostupná jen v omezené míře. Výsledek práce může pomoci odhalit možná rizika pro finanční stabilitu. Metody použité v této práci mohou být dále rozvíjeny a aplikovány na rozvíjející se ekonomiky, které čelí obdobným datovým omezením.

Klasifikace JEL: E37, G21, G28

Klíčová slova: bankovnictví, kreditní rizoko, makroekonomické zátěžové testování, míra defaultu, tržní riziko

Author's e–mail: tatjana.vukelic@seznam.cz

Supervisor's e–mail: petrjakubik@seznam.cz

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Abbreviations

BCBS Basel Committee on Banking Supervision
BMI Business Monitor International
BS Banking System
CAR Capital Adequacy Ratio
CB Central Bank
CDE Classified Assets of Categories C, D and E
CEBS Committee of European Banking Supervisors
CNB Croatian National Bank
CORP Corporations
CPI Consumer Price Index
EAD Exposure at Default
ECB European Central Bank
ESOP Employee Stock Ownership Plan
EU European Union
EUR Euro
Fed Federal Reserve System
FSAP Financial Sector Assessment Program
FSI Financial Soundness Indicators
FX Foreign Exchange
HH Households
HRK Croatian Kuna
IAS International Accounting Standards
IMF International Monetary Fund
KPSS Kwiatkowski–Phillips–Schmidt–Shin Test

LGD Loss Given Default

LLP Loan Loss Provision

NBS National Bank of Serbia

NPL Non–Performing Loan

OLS Ordinary Least Squares

PB Private Bank

PD Probability of Default

PPI Producer Price Index

QLR Quandt Likelihood Ratio Test

RAMSI Risk Assessment Model for Systemic Institutions

ROA Return on Assets

ROE Return on Equity

RSD Serbian Dinar

RWA Risk–Weighted Assets

SCAP Supervisory Capital Assessment Program

USD United States Dollar

VaR Value at Risk

WB World Bank

Chapter 1

Introduction

The launch of Financial Stability Assessment Program (FSAP) by the International Monetary Fund (IMF) and the World Bank (WB) in 1999 established macro stress tests as part of financial stability toolbox and brought them to the forefront of interest of national regulators and supervisors. Moreover, in light of recent financial crisis, stress tests that can quantify potential impact of adverse events on economy are highly discussed topics. Generally, macro stress tests measure risk exposure of financial system to severe but plausible shock. In that case they can help national authorities to reveal financial system's vulnerabilities. Central banks have usually their own stress–testing models and revise them on regular basis. So far, there is no consensus on how they should be set and how the results should be interpreted. The main challenge is how to set stress tests in order to capture reality in the most appropriate fashion. In most cases we are constrained by data availability and computation complexity.

Several studies have been already published, both theoretical and empirical ones. Surveys try to deal with stress–testing limitations and demonstrate the application of stress tests on hypothetical or real financial sectors. While financial systems of developed countries are subjects to continuous assessment, emerging markets has not been endowed with such an attention, yet. Emerging markets tend to be sensitive to various economic shocks and as a significant part of international investments goes there, the assessment of their financial health is of high importance.

This work analyses financial stability using stress tests in two Balkan countries. In the first draft of the work we planned to cover four countries: Bosnia and Herzegovina, Croatia, Macedonia and Serbia. However, we realised soon that the analysis of four countries would make the thesis too complex and, what is more, that crucial databases for Bosnia and Herzegovina and Macedonia are of limited use. Under these circumstances, we decided to conduct the exercise only for Croatian and Serbian banking sectors.

Following hypotheses has been investigated: (1) Stress tests for selected countries can be built up on the basis of publicly available data. (2) Some banks show insufficient capital adequacy under baseline and adverse scenario. (3) Stress tests can reveal risks to financial stability in selected countries. To analyse the hypotheses we identify relevant set of institutions that will be considered in both countries. Then, we design baseline and stress scenarios for one year horizon and quantify their impact on financial sector's solvency by integrating the analysis of multiple risk factors into a probability distribution of aggregate losses. From the range of risks that can be examined we focus on credit and market risks.

While the market risk is relatively easy to calculate, the credit risk, which is the main risk that financial institution faces, deserves a greater attention. Before the simulation of the impact of particular stress scenario on credit risk exposure, we usually need to link macroeconomic variables with relevant credit risk measures via so–called satellite models. Generally, there are two approaches how to build such models, Merton (1974) approach and Wilson (1997a,b) approach. The latter is employed in this study. We apply aggregate results of stress tests on individual banks' portfolios and interpret the outcome. At the end, we calculate potential feedback effects in terms of fiscal costs.

This Rigorous Thesis is based on Master Thesis defended at Charles University in Prague in June 2011. Regarding very good supervisor's and opponent's evaluations without any comments about its structure or content we have not changed the original thesis a lot. We shortened the theoretical part of the work slightly. On the other hand, we added a short chapter before concluding remarks that compares our findings from the spring 2011 with the recent development in Croatia and Serbia in autumn that year.

The thesis is structured as follows: Chapter 2 provides an overview of related literature. Chapter 3 describes general theoretical background of the stress tests. Chapter 4 develops macroeconomic credit risk models for corporate and household sectors for each country that serve as satellite models in stress testing. Chapter 5 consists of specification of scenarios and stress–testing analysis. Chapter 6 shows results of stress tests on individual banks. Chapter 7 provides a comparison of our results with real economic development at the end of 2011. Chapter 8 concludes and discusses possible future research.

Chapter 2

Related Literature

In the last ten years, several studies that deal with macro stress–testing methodology have been published. As a part of financial stability assessment, macro stress tests were introduced in the FSAP 1999 (see i.e. IMF & WB 2003). After the introduction of the FSAP, national regulators and supervisors started to incorporate stress tests into their periodical financial stability assessments. Many studies have highlighted the usefulness of stress tests in macro–prudential analysis. For example, Borio, Furfine & Lowe (2001) point out the importance of stress tests in improving the understanding of risk and its relationship with business cycle. One of the largest stress–testing exercise was conducted by legal authorities in the EU and the USA after recent financial crisis in order to evaluate current conditions of their financial systems (Fed 2009a,b and CEBS 2010a,b).

Discussion about objectives, modelling process and challenges of macro stress tests can be found in Drehmann (2008). Sorge & Virolainen (2006) discuss two main approaches to stress testing, the econometric analysis of balance–sheet data (balance–sheet models) and the Value–at–Risk (VaR) models, and apply both of them to Finish economy. In the balance–sheet models macro variables are linked with balance–sheet items. Obtained coefficients are then used to simulate the impact of some shock to the system. The VaR models combine risk factor analysis with estimation of distribution of loss, providing the quantification of portfolio sensitivity to several sources of risk. Čihák (2007) elaborated a comprehensive framework that concerns on design of stress tests and scenarios, assuming a wide range of risks. He provides the illustration of possible stress–testing application to bank's data. The paper discusses strengths and weaknesses of several methods and provides the summarisation of stress tests methodologies of various national authorities all around the world. Sorge (2004) provides an overview of methodologies for tress testing the financial systems, and discusses methodological challenges such as the measure of endogenous risk or the correlation between credit and market risks. Berkowitz (2000) discusses namely the choice of proper scenario under which stress tests are conducted.

Regarding the empirical studies, most of them consider credit risk within macro stress tests. Before the simulation of impact of stress scenario on credit risk exposure is run, the linkage of macroeconomic variables (such as GDP growth, interest rates, unemployment, industrial production, inflation etc.) with relevant credit risk measures via satellite models should be investigated. There are several approaches to set up such models, usually called macro credit risk models. Drehmann (2005) and Čihák (2007) highlight, among others, a non–linear relationship between macroeconomic shocks and credit risk in macroeconomic credit risk models. Some studies have developed Merton–type credit risk models based on modelling of asset return. Merton (1974) originally designed the model to price several types of financial instruments. The idea of Merton–type model is to define the default event as a fall of asset return below defined threshold. Latent–factor model of Merton's type for the Czech economy is used in Jakubík (2007). Jakubík & Schmieder (2008) model the default rate that is measured by the inflow of non–performing loans (NPLs). The model was applied to household and corporate sectors for the Czech Republic and Germany. Hamerle, Liebig & Scheule (2004) use the factor–model based on Basel II approach for forecasting default probabilities of individual borrowers in Germany. Merton–type model is used in Drehmann (2005) for analysing corporate exposures of UK banks.

Other studies follow approach originally introduced by Wilson (1997a,b).[1] Wilson's model is one of the few models that explicitly links default rate with macroeconomic variables and it is based on relatively simple logistic function used in regression analysis. Also Čihák (2007) suggests the logistic model for estimating inputs to stress–testing modelling. Wilson–type model is employed in Boss (2002) and Boss *et al.* (2006). These studies estimate relationship between macroeconomic variables and credit risk for corporate default rate in Austrian banking sector. Later on, Boss *et al.* (2009) discuss the update of stress–testing model for the Austrian National Bank. Virolainen (2004) and Jokivuolle, Virolainen & Vähämaa (2008) develop the macroeconomic credit

[1] Model known as CreditPortfolioView®, developed for McKinsey & Company.

risk model that estimates the probability of default in various industries as a function of macroeconomic variables for Finish economy. Similarly, our study is based on Wilson's logistic credit risk model.

Apart from studies discussed above, there are several other surveys that investigate the relationship between macro variables and banks' balance–sheet items. Babouček & Jančar (2005) employed the vector autoregression model (VAR) using NPLs and macroeconomic factors for the Czech Republic. Pesola (2005) investigates the macroeconomic factors that influence banking sector's loan loss rate in the Nordic countries, Germany, Belgium, the UK, Greece and Spain using panel–data regression on data from early 1980's to 2002. Evjen *et al.* (2005) analyse the effects of monetary responses to supply and demand side shocks on banks' losses in Norway and discuss how stress tests can be incorporated into monetary policy decision–making.

Some studies aim to incorporate more sources of risks into one model. One of earlier studies is Barnhill, Papapanagiotou & Schumacher (2000). The authors measure correlated market and credit risks and apply results to hypothetical South African banks, linking the changes in financial conditions to banks' capital ratios. Study of Van den End, Hoeberichts & Tabbae (2006) describes the multivariate scenario analysis (deterministic and stochastic) and stress tests used by the Dutch Central Bank. The study estimates the probability of default (PD) and the loss given default (LGD) employing the logistic function, and models both credit risk and interest rate risk. Also Drehmann, Sorensen & Stringa (2008) estimate the integrated impact of credit and interest rate risks on banks' portfolios, assessing banks' economic value, future earnings and capital adequacy. They expand the analysis of interest rate risk and default risk on liabilities and off–balance sheet items. Peura & Jokivuolle (2003) measure capital adequacy by analysing the difference between bank's actual capital and minimum capital requirements. They determine whether the estimated capital buffer is sufficient over the business cycles. The Bank of England works on the model of systemic risk called RAMSI (Risk Assessment Model for Systemic Institutions), which incorporates credit risk, interest and non–interest income risk, network interactions and feedback effects. The RAMSI model tries to eliminate some of the shortcomings of macro stress–testing models. Study of Aikman *et al.* (2009) discusses liability–side feedback effects in systemic risk models and how these feedbacks can lead to higher system instability under the RAMSI model.

Chapter 3

Theoretical Background

3.1 Role of Stress Tests in Financial Stability Analysis

Stress testing is a technique used both by banks' risk managers and financial sectors' authorities to assess vulnerabilities of particular bank or the whole financial system under severe but plausible shocks. Stress tests were originally developed within risk management departments in banks. As a part of the FSAP, they have been recognised by regulators and supervisors as standard tools in financial stability analysis. Our study concerns on stress testing of financial systems, commonly known as "macro" stress testing.

Macroeconomic forecasting, early warning systems and macro stress tests come under financial system's toolbox for assessing financial stability and its threats and strengths. Macroeconomic forecasting is based largely on analyses of historical macroeconomic data in order to project the most likely future performance of economy. Forecasting models can be used also in stress testing as a part of scenario analysis. Early warning systems and stress tests differ from macroeconomic forecasting, as they focus on unlikely but plausible events. Both aim to generate *ex ante* warnings about possible problems that might appear in the future. Early warning systems consists of indicators that can help to estimate probability of an unlikely crisis. Firstly, they define the crisis by setting up threshold values for relevant macroeconomic variables and then they estimate probability of breaking down the thresholds. Early warning models are usually based on historical data. Stress testing can be based either on historical data or on hypothetical scenarios. It simulates some severe adverse but plausible situation in order to assess the vulnerability of financial system under this situation. It does not analyse the probability of such crisis but its consequences for financial stability. Detailed discussion about monitoring systems is provided i.e. in Sahajwala & Van den Bergh (2000). Following chapter aims to provide theoretical background of stress–testing methods.

3.2 Building Blocks of Stress–testing Models

Macro stress tests measure the risk exposure of financial institutions (or selected group of financial institutions) to unlikely stress events. Their goal is to help regulators and supervisors to identify system vulnerabilities and overall risk exposures that can lead to problems with financial stability. Macro stress–testing framework can be described as follows: Firstly, we assume some shock to economy. Using the macroeconomic model we link the shock to macroeconomic variables such as GDP, interest rates, inflation etc.[1] Assumed macroeconomic variables are then linked to banks' balance–sheet data through satellite models. Then, we map the effect of shock into banks' financial performance and we estimate possible impacts in terms of i.e. minimum capital adequacy ratio (CAR).

Formally, stress–testing models can be written as follows (see Sorge 2004, pp. 3–4):

$$\Omega\left(\tilde{Y}_{t+1}/\tilde{X}_{t+1} \geq \bar{X}\right) = f(X^t, Z^t) \tag{3.1}$$

where X^t is the set of past realisations of macroeconomic variables X, Z^t is the set of past realisations of other relevant factors, $\tilde{Y}_{t+1}$ is the measure of distress for financial system, $\tilde{X}_{t+1} \geq \bar{X}$ is the condition for stress test scenario to occur, $\tilde{Y}_{t+1}/\tilde{X}_{t+1} \geq \bar{X}$ is the uncertain future realisation of the measure of distress in event of shock, $\Omega(.)$ is the risk metric used to compare financial system vulnerability across institutions and scenarios and $f(.)$ is the loss function that maps initial set of shocks to final impact measured on financial sector's portfolio. It links changes in macro variables and overall financial distress.

The starting point when we model stress tests is to define the scope of analysis (objectives, set of institutions or portfolios to be analysed, exposures and risk measures and data–generating process). Exposures are given by the

[1] Sometimes, macroeconomic models are not available. In that case we can employ vector autoregression (VAR) or vector error correction models or we can simply use historical observations during the periods of distress or we can expertly judge the movements of macro variables.

set of exogenous systematic risk factors. Data–generating process of systematic risk factors finds interdependences among these factors and across time. Accordingly, the impact of factors on risk measure of exposures is captured. Stress–testing scenarios are applied when the model is set up. After designing and calibrating scenario we estimate direct impact of scenario on balance–sheet items. New approaches try to evaluate possible feedback effects both on financial system and real economy (i.e. in terms of fiscal costs).

3.2.1 Bottom–up vs. Top–down Approach

There are two approaches how to set up macroeconomic stress tests. In the bottom–up macro stress tests, the supervisor (i.e. central bank) sets assumptions about future economic conditions for stress tests. It approves individual bank's internal models and other assumptions for exercising the test. The stress test itself is conducted by banks and the supervisor collects results afterwards. In the top–down approach, the supervisor not only sets up conditions but also conducts the stress test, applying the same assumptions, procedures and models on all banks.[2].

As an example of the bottom–up approach is recent stress–testing exercise of the Fed (2009a,b). Banks were provided with basic assumptions and their internal methods were subject to approval of the Fed. Nevertheless, it was the bank who conducted the exercise and provided the supervisor with results, which were then summarised and published. The top–down approach can be found i.e. in Sorge & Virolainen (2006). Some central banks use the combination of both approaches, for example the Dutch Central Bank (see Van den End, Hoeberichts & Tabbae 2006).

The top–down and the bottom–up approaches have their pros and cons. The main advantage of the top–down approach is that the same assumptions and models are applied to all banks, which allow for comparison. Also, the network linkages can be captured. The disadvantage of the top–down approach is that conducting stress tests on system's level can lead to the loss of some relevant information, being this confidential or too complex to be captured by the supervisor. The bottom–up approach can capture complexities better and usually does not suffer from data limitations because detailed data on individual debtors are available in banks. The disadvantage is that individual bank's results need not to be comparable as banks possess certain level of freedom

[2]See Čihák (2007) and Jakubík & Sutton (2011).

in choosing models and methods in the exercise. Also the supervisor might not be able to control the consistent implementing of assumptions that were provided, especially in large financial systems. Moreover, the summarisation of individual bank's outcomes can neglect important interdependencies among these institutions.

3.2.2 Objectives

Drehmann (2008) identifies three main objectives of stress tests: (1) validation – to assess risks and portfolio's vulnerabilities, (2) decision making – test results can help in business decisions and planning, and (3) communication – results can describe overall situation in financial institution or in the whole sector and can be communicated to target audience. As Drehmann argues, the objectives are essential for designing the models. If our main target is to validate the situation and to make decision according to results of the model, this model should be accurate and with good forecasting performance (the use of robust econometric techniques and structural models might be appropriate). But if we run the model and we want to present the results to the public, which may not be involved in the process, the model and its results should be transparent, easy to understand and tractable (reduced–form models are more appropriate).

Before the model is set, the group of relevant financial institutions, which we want to analyse, should be defined. Capturing the whole financial sector is more comprehensive, but usually difficult to accomplish. Modellers frequently choose only large banking institutions that are relevant for stability of the system. Sometimes, distinction between state–owned, private and foreign banks is done (see Čihák 2007). Banks can be grouped by their size (large, medium–size or small banks) or performance (strong banks and weak banks). Next, we define relevant portfolio for measuring risk exposures (trading books or banking books). Sometimes data limitations lead to creation of hypothetical portfolios that simulate distribution of assets and risk exposures. Some models distinguish exposures by debtor's classes (consumer loans, interbank loans, corporate loans further divided by industrial sectors), see for example Boss (2002), Sorge & Virolainen (2006) or Jakubík & Schmieder (2008).

3.2.3 Exposures

The objectives of stress test determine the choice of exposures. Ideally, the model would capture the whole financial system and would assess its most important risks. Given data and model limitations (every model is able to capture real world only in a reduced form) this task is difficult to achieve. Usually, we choose only the part of system and we make simplifying assumptions in order to create the model and run the test. Common approach is to test banking system because it usually counts for major part of financial system, and as Drehmann (2008, p. 67) argues *"because of its pivotal role in the transformation of savings into investments and, hence, its position in transmitting financial system shocks back to the real economy"*. Some authors test also other sectors of financial system. For discussion about modelling of insurance and pension sectors see Čihák (2007).

Major part of stress–testing models copes with the risk within national system. Stress testing of single financial system benefits from better data availability, and can provide the implications for policy decision–making. Still, some studies focus on international macro stress–testing models. Pesaran *et al.* (2006) have developed the model where asset values of credit portfolios are linked to dynamic global macro model.

The risks to which financial institutions can be exposed can be summarised in five categories: credit risk, market risk, liquidity risk, contagion risk, and concentration risk. So far, majority of studies focused on credit risk (Drehmann 2005, Pesaran *et al.* 2006 or Jakubík & Schmieder 2008). However, some authors try to incorporate more risks in stress–testing models. Drehmann *et al.* (2008) have incorporated credit and interest rate risks and estimated their impact on banking system. Čihák (2007) runs stress–testing model to assess vulnerabilities of hypothetical banking system, using several risks, which have been analysed separately. Nevertheless, for more realistic forecasting the correlation of risk factors should be evaluated. Measures of correlated market and credit risks can be found in Barnhill, Papapanagiotou & Schumacher (2000) or Van den End, Hoeberichts & Tabbae (2006).

So far, stress tests focused mainly on asset side of balance sheets. Liability side is, however, essential for modelling liquidity risk (maturity mismatch between assets and liabilities can cause serious problems with liquidity for a bank) and for analysing net interest income. Similarly, off–balance sheet positions are important when calculating exchange rate risk losses.

3.2.4 Risk Measures

Assessment of risks to financial sector can be done through simple indicators, i.e. Financial Soundness Indicators (FSIs), or through stress testing.[3] The FSIs are based on balance–sheet and income–statement data, information about ownership structure and linkages between institutions (for example, non–performing loans (NPLs), loan loss provisions (LLPs), return on assets (ROA), return on equity (ROE), net open positions in foreign exchange etc.). The FSIs provide the overall picture of soundness of banks and financial sectors. The overview of financial soundness indicators, as were defined by the International Monetary Fund (IMF), is provided in Table A.1 and A.2 in Appendix A. Table A.1 shows the core FSIs. They cover only banking sector and are essential to assess its financial stability. Table A.2 summarises additional FSIs that cover data on other financial institutions and relevant market participants (households, real estate sector, non–bank financial sector, corporate sector etc.). Each FSI measures financial system's sensitivity to specific risk factor (liquidity risk, market risk etc.). In order to assess all vulnerabilities it should be appropriate to analyse several FSIs and also the inter–relationships among them.[4]

The choice of risk measures is determined by objectives of stress testing and considered exposures. Moreover, variables used as measures of the impact of stress tests are subjects to data limitations. According to Čihák (2007), risk measure should fit two requirements: (1) the possibility to interpret variable as a measure of financial system's health, and (2) the credible linkage of variable to risk factors. Čihák (2007) also provides the overview of risk measures commonly used in stress testing. We will discuss some of them briefly. The list described below is incomplete as it provides only few indicators. For more indicators such as net interest income, z–scores or market–based indicators we refer to Čihák (2007).

Capital, capitalisation and capital injection. The use of capital as a measure of the effect of shock is an instinctive approach, arising from the fact that the impact on solvency results in changes in capital. The advantage is that data on capital are usually publicly available for financial institutions in developed as well as in developing countries. The disadvantage is that the result is provided as a number and it might be necessary to compare it to some

[3] Čihák (2007) considers also individual bank's z–scores, which are directly linked to probability of bank's insolvency.

[4] For detailed discussion about the FSIs, see IMF (2006).

other variable in order to assess the impact of shock. One of possibilities is to divide the capital by assets or risk–weighted assets (RWA). The advantage of capital adequacy ratio is that it is commonly accepted indicator of financial health. Another option is to divide the capital by some macroeconomic factor (i.e. GDP). Such indicator provides direct link to macroeconomy. In our study we use this indicator as a measure of potential fiscal costs from banks' failures under the shock.

Profits and profitability. During the "good" times, banks usually create profits. In the case of distress, profits can serve as the first buffer against losses before the capital is employed. Accordingly, it could be useful to express the shock in terms of capital and profits. The disadvantage when estimating the profits is that often we do not know what amount of profit would banks keep and what amount would distribute. That results in approximation of profits by past values or some other indicators. The measure scaled by bank's size (i.e. return on equity or return on assets) allows for comparison across institutions.

Ratings and probabilities of default. Ratings and probabilities of default (PDs) allow for combining solvency and liquidity risks into a single measure. The indicators are useful as they translate changes in variables into changes in ratings and if we link ratings with PDs, the impact of shock on PDs can be estimated.

Banks set the capital against all risks that they face (credit, market, operational, business risk etc.). Yet, not all of them are included in stress–testing model. The indicated capital buffer can be too large since it goes to all risks but the model considers that it is spent only on analysed risks. The aggregation of variables is problematic issue, too. Testing aggregate capital adequacy of financial system may not reveal significant vulnerabilities concerning individual institutions and the whole system. The use of size–weighted average can help to assess risks properly (insolvency of a small bank is not alarming for the system as a whole while big insolvent players can cause serious system instability through contagion effect and can become subjects to policy actions).[5]

In stress tests we assume that market agents are passive when the shock occurs. That means that we assume they do not change their behaviour in the light of crisis. In reality this is not usually valid. In order to maintain this assumption as realistic as possible we should think carefully about time horizon over which stress tests will be run. The integration of endogenous behaviour

[5]Drehmann (2008, pp. 69–70).

of market participants and policy makers into the model is one of the greatest challenges for stress–testing development. We discuss it in detail in Section 3.5.

3.3 Stress–testing Scenario

Another challenge in stress testing is the choice of scenario. The adverse scenario should be severe enough to uncover risks to financial stability but still plausible. Selected shock can be a univariate shock in single risk factor, such as decline in equity prices. The shock can be also multivariate, reflecting the change in various risk factors. The multivariate scenarios are often more realistic because they allow for interaction of variables. According to Berkowitz (2000) there are four types of scenarios (list was developed for models that focus on assessing the robustness of capital):

1) Scenario that simulate shocks which we believe are more likely to happen than observed historical data suggest;

2) Scenario that works with shocks which have never occurred;

3) Scenario that simulate shocks which represents the possibility of a break–down of statistical patterns under some circumstances (structural breaks of states of the world);

4) Scenario that simulate shocks that express some structural breaks, which can occur in the future (i.e. change of exchange rate regime).

Čihák (2007) distinguishes between two ways how to design consistent scenario. The first way is the "worst case" approach that answers the question of which scenario has the worst impact on financial system, with given level of plausibility. Alternatively, there is the "threshold approach", which for a given impact on system creates the most plausible scenario that would lead to that impact. Level of plausibility can be set according to historical observations. Alternatively, scenarios can be drawn from data–generating process or some variables can be set expertly.

Extreme historical events are easy to communicate and implement. Under historical scenarios we could estimate behaviour of market participants more properly, because their behaviour could be similar to that observed in the past. Also, historical scenarios are severe but plausible, as they have already happened in the past. Another, and direct, option that utilise historical data is to plot observed risk factors against the measure of system's financial health (i.e. CAR, NPLs) and to pick the most adverse combination of risk factors.

This method can, however, lack consistency as identified observations can be from completely different historical periods. The main disadvantage of using historical scenarios is that it is uncertain if the same situations would repeat in the future.

For developing scenario through data–generating process, Drehmann (2008) identifies four main methods that can be employed: (1) calibrated distributions of unobserved factors, (2) autoregressive processes for each underlying macro variable, (3) reduced form vector autoregressive macro models, and (4) structural macro models. Specifically, for communication purposes macro models are more suitable than modelling the unobservable factor. Macro models can show important macroeconomic transmission channels but can be relatively complex, too. In turn, autoregressive models do not include interdependences of systemic risk factors but, as Van den End, Hoeberichts & Tabbae (2006, p. 3) argue, the structure of scenario does not provide for economic foundation. The choice of the model depends on stress test's objectives and on systematic risk factors that are assumed.

3.4 Review of Methodological Approaches to Macro Stress Testing

The methodology discussed in this section concerns on top–down approach to stress testing. Sorge (2004) and Sorge & Virolainen (2006) distinguish between two methodological approaches how macro stress tests can be modelled. The first is the "piecewise approach" that considers balance–sheet models. These models analyse direct link between banks' accounting items (NPLs, LLPs etc.) that measure their vulnerability and business cycle (GDP growth, unemployment etc.). Secondly, there is the "integrated approach" that applies Value–at–Risk (VaR) models. In VaR models multiple risk factors are combined into mark–to–market probability distribution of losses that financial system could face under given scenario.

Balance–sheet models are widely used in stress tests. Estimated coefficients can be employed to simulate the impact of macro shock on financial sector. Balance–sheet models can be either structural models or reduce–form models. The VaR models are relatively complex and combine the multiple risk factors (credit risk, market risk etc.). Both approaches are discussed in this section, in line with the studies of Sorge (2004) and Sorge & Virolainen (2006).

3.4.1 Balance–sheet Models

Balance–sheet models are based on estimation of balance sheets' sensitivity to adverse change in crucial macroeconomic variables. Estimated coefficients are used to simulate the impact of hypothetical scenarios on financial system.

Balance–sheet models can be in reduced form, using either time–series or panel data methods, or economy–wide structural models. Both of them link system's vulnerability (bank losses) to changing macro variables.[6] The advantage of balance–sheet models is that they are intuitive and easy to implement. On the other hand, they are usually expressed in linear form, although the relationship between banks' risks and macro variables is rather non–linear.[7] Moreover, they frequently investigate expected losses and do not consider the whole loss distribution. We provide a brief discussion about each type of balance–sheet model.

Time series models. Time series models are suitable for assessing the concentration of system portfolio's vulnerabilities over time. The most common measures are NPLs, LLPs or composite indices of balance–sheet and market variables. Loan loss provisions or other variables can be linked to macro indicators such as GDP, output gap, unemployment, inflation, income, consumption and investment, or interest and exchange rates. As an example, for stress–testing of Austrian banking sector, Kalirai & Scheicher (2002) analysed aggregate LLPs as functions of the set of macro variables using the time series model.

Panel data models. Panel data models analyse individual bank's portfolio or aggregate banking systems across countries, evaluating the role of bank–specific or country–specific risk factors. Again, dependent variables could be LLPs, NPLs or indicators of profitability. Dependent variables are often not only functions of macroeconomic variables but also of bank–specific factors (size, portfolio diversification, specific clients etc.). The cross–sectional dimension enables to evaluate the impact of shock on banks' health according to their specific characteristics (size or client's orientation). Pesola (2005) investigates macroeconomic factors that influence banking sector's loan loss rate in the Nordic countries, Germany, Belgium, the UK, Greece and Spain using the panel–data regression.

Structural macro models. Structural macro models are able to capture

[6] Sorge & Virolainen (2006, p. 119).

[7] For example, Drehmann (2005) found that systematic factors have non–linear and non–symmetric impact on credit risk.

complex relationships in stress testing, and thus can better show the correlation between shock and relevant macro variables or structural interdependences. Hoggarth & Whitley (2003) analyse the impact of liquidation rates on write–off rates through reduced–form model, whereas the shock to macroeconomy was analysed by macroeconomic model and structural model linked macro factors to liquidation rates afterwards. De Bandt & Oung (2004) have developed similar model for France. Some authors combine micro and macro models. In Evjen *et al.* (2005) micro models are used to estimate individual firm's probability of default that is based on actual balance–sheet data (operating income, interest expenses, long–term debt etc.) and company size or industry characteristics. proxies for debt–servicing capacity of corporate sector are used to estimate banks' loan losses. The overall model then estimates the impact of demand and supply shock in banking system.

3.4.2 Value–at–risk Models

VaR macro models represent extension of VaR models adopted in financial institutions. Models are based on estimation of conditional probability distribution of losses for different stress scenarios. Value at risk then, as a summary statistic of this distribution, measures the sensitivity of portfolio to different risks.

VaR approach allows for non–linear relationships between macro variables and indicators of financial stability. Also, it allows for integration of credit and market risk in one model. The shortcoming of VaR models is the non–additivity across portfolios when models are applied to individual banks.[8] Thus, for the analysis of banking system, aggregated portfolio is usually used. However, running the model on aggregate level might neglect the contagion effect that could occur among institutions.

For VaR models, Sorge & Virolainen (2006) highlight two approaches that explicitly link default probabilities to macro variables. Wilson (1997a,b) approach allows to model directly the sensitivity of default probabilities to evolution of the set of macro variables. Merton (1974) approach firstly models the response of equity prices to macro variables and then translates asset price changes into probabilities of default.

Merton (1974) approach. Merton's model was originally developed for

[8] The VaR of bank's consolidated portfolio does not equal to the sum of individual bank's VaRs due to correlations among them.

the firm's level. After him, the approach was extended for purposes of macro stress–testing. Merton's models are frequently set as follows: Firstly, we make some assumptions about the joint evolution of macro and market factors. These factors are then linked to corporate return on equity through the multi–factor regression on panel of firms. Finally, equity returns enter the model to estimate individual firms' probabilities of default. Merton–type model for the Czech economy was used in Jakubík (2007). Jakubík & Schmieder (2008) apply the model on household and corporate sectors for the Czech Republic and Germany. Hamerle, Liebig & Scheule (2004) used factor–model to forecast default probabilities of individual borrowers in Germany. Merton's model was used also in Drehmann (2005) for stress testing corporate exposures of banks in the UK.

Wilson (1997) approach. Wilson's approach consists of modelling the relationship between default rate and macro variables. Accordingly, we generate shocks and simulate the evolution of default rates, which are at the end applied to particular credit portfolio. Wilson's approach is intuitive and not computationally demanding as Merton–type models. Wilson's logistic model was used in studies of Boss (2002) and Virolainen (2004). Boss (2002) and Boss *et al.* (2006) estimated relationship between macroeconomic variables and credit risk for corporate default rate in Austrian banking sector. Virolainen (2004) and Virolainen, Jokivuolle & Vähämaa (2008) develop the macroeconomic credit risk model that estimates probability of default in various Finish industries.

Integrated market and credit risk analysis. Changes in macro fundamentals can influence market value of banks' assets and liabilities directly but also indirectly. Indirectly, they affect the indebtedness ratios of households and firms, which change credit risk exposures of banks. Sorge & Virolainen (2006, p. 127) argue that the incorporation of macro variables in credit risk models implicate that these models analyse both market and redit risks. Wilson's and Merton's models implicitly incorporate credit and market risks. There are studies which try to reflect the two risks more explicitly, for example Barnhill, Papapanagiotou & Schumacher (2000). Their findings indicate that market risk, credit risk, portfolio concentration, and asset and liability mismatches are all important but not additive sources of risk. Accordingly, they should be evaluated as a set of correlated risks.

3.5 Limitations and Challenges

Stress testing, as a relatively new technique, faces many limitations and challenges. The main shortcomings of macro stress tests are frequent data limitations, inability of models to capture the correlation of risks and risk measures over time and across institutions and to interpret results in longer time horizon. Next, endogenous behaviour of market agents and macro feedbacks, forecasting limitations of reduced–form models and computational problems of structural models are all problematic issues. Last but not least, the incorporation of model's implications in policy decision–making is only partial. Complex discussion of limitations and challenges of current stress tests can be found in Sorge & Virolainen (2006), Čihák (2007) or Drehmann (2008).

3.5.1 Data Availability and Time Horizon

Data that are essential for stress testing are limited in several ways. First of all, severe historical shocks are rare. Historical data are of limited use. Frequently, the adjustment of model by additional assumptions that are set by expert judgment or based on data–generating process is needed. Secondly, financial markets develop rapidly and it is difficult to track all changes. Financial institutions' data are often not available (at least for public use). Some of them (i.e. data on individual clients) can be confidential. Even provided data need not to be exact or comparable with data from other institutions. The model can break down during the shock as some characteristics, observed in the past, can change (i.e. borrowers' repayment discipline). Data limitations should be taken into account when setting–up and running models. The use of standard parametric econometric models with insufficient data leads to non–robust estimates and large errors, which in turn reduce forecasting ability of models.

Regarding time horizon, there exists a trade–off between predictive power of model and ability of shock to fully translates into deterioration of banks' financial performance. The crisis usually evolves over time and it takes even some years to show its whole impact. But when considering longer time horizon, problems with endogenous responses of the system emerge. It is not unlikely that banks would take steps to decrease losses if they once recognise the crisis, even though if its impact did not fully emerge.

3.5.2 Endogeneity of Risk

Drehmann (2008) provides three reasons why the endogeneity of risk emerges in stress testing. It happens because of (1) endogenous behaviour of market agents, (2) lliquidity risk, and (3) macro feedbacks. The endogeneity of risk causes that the impact of exogenous shocks can be disproportional. The endogenous behaviour of agents shows that they are not passive when the shock occurs. For example, banks can fight against losses that arise from the crisis by hedging or realigning portfolio when some assets or liabilities mature. The liquidity risk may emerge as a response of endogenous behaviour in the market (i.e. run on weakly performing banks in case of panic in the market).

Macro feedbacks reflect the linkages between real economy and financial sector. In stress tests we assume the impact of macroeconomy on financial system (often called as the first round effect). The second round effect is the impact of stressed financial sector on macroeconomy. Difficulties with macro feedbacks lie in their complexity due to heterogenous market agents that respond differently on stimulations. Frequently, the second round effect is expressed as the injection needed to bring particular banks to regulatory minimum requirements (i.e. CAR). The injection needed does not cover all feedback effects but it is a useful tool how to assess potential fiscal costs of distress.

Chapter 4

Macroeconomic Credit Risk Model

4.1 Theoretical Framework

The credit risk model developed in this study is based on approach originally introduced by Wilson (1997a,b).[1] Wilson's model is one of few models that explicitly links default rate with macroeconomic variables and it is based on relatively simple logistic function that is used in regression analysis. It was empirically shown that non–linear logistic function is more suitable for analysing relationships in the model than linear functions. Wilson's model was further used in Boss (2002) or Virolainen (2004). Also Čihák (2007) suggests logistic model for estimating inputs to stress–testing modelling. We will discuss the model briefly, however, for more detailed discussion, we refer to Wilson (1997a,b).

The idea of macro credit risk model is as follows: We assess credit risk, which is expressed by default rate, in dependence on macroeconomic variables.[2] We simulate the future default losses according to changing macroeconomic situations. We test macroeconomic variables for possible correlations in order to reveal existing interdependences. The outcome of model is used as a basis for macro stress testing in Chapter 5.

Default rate or default probability, defined as a portion of "bad" loans to total loans in banking system, is in our model shown as a ratio of non–performing loans (NPLs) to total loans (NPL ratio). Default rate is regressed against various macroeconomic variables in order to estimate their impact on aggregate banking sector portfolio. We run the model for household and corporate sectors

[1] Model known as CreditPortfolioView®, developed for McKinsey & Company.

[2] We assume that more than one variable affects dependent variable, thus, we can call the model as a multi–factor model.

separately in order to detect specific factors that influence credit risk in these two sectors.[3] We do not consider lending to government sector, since it is in general considered as a type of lending that does not carry any default risk.

Our model estimates sector–specific default rate using logistic function of sector–specific index, which depends on values of macroeconomic variables:

$$npl_{s,t} = \frac{1}{1 + e^{-y_{s,t}}} \tag{4.1}$$

which can be re–written as:

$$ln\left(\frac{npl_{s,t}}{1 - npl_{s,t}}\right) = y_{s,t} \tag{4.2}$$

where $npl_{s,t}$ denotes NPL ratio (default rate) of sector s and $y_{s,t}$ is sector–specific index of sector s at time t. Contrary to Virolainen (2004), but in line with Boss (2002), we adopt the formulation of sector–specific index in such a way that lower value of $y_{s,t}$ implies better state of economy with lower default rate $npl_{s,t}$.[4]

Index $y_{s,t}$ represents the overall state of economy, and it is the linear function of exogenous macroeconomic factors:

$$y_{s,t} = \alpha_s + \beta_s x_{s,t} + \epsilon_{s,t} \tag{4.3}$$

where α_s is intercept, $\beta_s = (\beta_{s,1}, \beta_{s,2}, ..., \beta_{s,n})$ is set of regression coefficients related to set of sector s–specific macro explanatory variables $x_{s,t} = (x_{s,1,t}, x_{s,2,t}, ..., x_{s,n,t})$, and $\epsilon_{s,t}$ is random error, which is assumed to be independent and identically distributed $\epsilon_{s,t} \sim N(0, \sigma_\epsilon^2)$.[5]

The model described above is suitable for stress testing as it respects empiri-

[3] The separation of credit risk modelling for household and corporate sector was used i.e. in Jakubík & Schmieder (2008). Some authors run the model on individual industrial sectors, see Virolainen (2004).

[4] The formulation leads to negative coefficients for variables to which the NPLs ratio is inversely proportional (i.e. GDP growth) and positive coefficients for variables to which the NPLs ratio is directly proportional (i.e. interest rate).

[5] Some authors further model the development of individual macroeconomic factors in time as a set of univariate autoregressive equations of second order AR(2):

$$x_{j,t} = c_{j,0} + c_{j,1} x_{j,t-1} + c_{j,2} x_{j,t-2} + \nu_{j,t}$$

where $c_j = (c_{j,0}, c_{j,1}, c_{j,2})$ is set of regression coefficients related to j–th macroeconomic factor, and $\nu_{j,t}$ is random error assumed to be independent and identically distributed $\nu_{j,t} \sim N(0, \sigma_\nu^2)$ (see Boss 2002 or Virolainen 2004). The purpose of the model is to estimate macro variables's future values, which are applied to credit risk model. We do not consider macro variables's modelling as we obtain projected values from economic forecasting (i.e. Consensus Forecast) in case of baseline scenario, and from historical volatility analysis for cally demonstrated fact that the probability of default is higher in "bad" times and lower in "good" times. Moreover, it separates corporate and household sectors, which usually react to macroeconomic shocks in different ways.

4.2 Data

Our credit risk model is based on quarterly data. Dependent variable in the model is ratio of banking sector's non–performing loans (NPLs) to total loans (default rate) with respect to sector to which it refers (either corporate sector or households).[6] Explanatory variable is sector–specific index, composed of various macroeconomic variables. Macroeconomic data are quarterly data, defined as a percentage change in actual value compared to corresponding period of previous year, thus derived on year–to–year basis.[7] Time series that were used were generally reported in National Banks' or Statistical Offices' databases and publications.

4.2.1 Croatia

Quarterly macro data for Croatia are based on rate of growth in given quarter relative to corresponding quarter of previous year. They were obtained from Croatian National Bank (CNB)[8], National Statistical Office[9] and Eurostat[10]. Namely, for corporate sector the macro factors include: 1) real GDP growth rate in Croatia and in the EU 15[11], 2) growth rate of nominal and real effective exchange rates, 3) growth rate of nominal HRK/USD and HRK/EUR exchange rates, 4) growth rate of nominal and real short–term and long–term lending

adverse scenario. Moreover, we have not found macroeconomic factors in our analysis to follow AR(2) process.

[6]It would be more convenient to use as a dependent variable the first difference of NPLs. However, given the logistic form of credit risk model, such variable would show negative values, which are not allowed for the logistic function.

[7]Note that data that are not derived on annual basis should be seasonally adjusted before the analysis starts.

[8]Available at: http://www.hnb.hr

[9]Available at: http://www.dzs.hr

[10]Available at: http://epp.eurostat.ec.europa.eu

[11]EU 15 is composed of: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal, Spain, Sweden and United Kingdom. We prefer to use this composition of the EU in order to avoid changes in time series due to EU enlargements. Real GDP growth rate of the EU is considered due to large foreign trade between Croatia and the EU.

interest rates for corporate loans, 5) inflation measured by Consumer Price Index (CPI)[12], and 6) growth rate of interest rate spread[13].

For household sector in Croatia we consider following macro determinants: 1) real domestic GDP growth rate, 2) growth rate of nominal and real effective exchange rates, 3) growth rate of nominal HRK/USD and HRK/EUR exchange rates, 4) growth rate of nominal and real short–term and long–term lending interest rates for household loans, 5) inflation measured by CPI, 6) growth rate of unemployment rate [14], 7) real wage growth rate, and 8) disposable income growth rate. The credit risk model for corporate and household sector in Croatia has been estimated using quarterly observations from Q1 2000 to Q2 2010 (42 observations sample).

Dependent variable in Croatian credit risk model is quarterly default rate measured by ratio of NPLs to total loans in particular sector (firms or households). Data on NPLs has been available only on aggregate basis, apart from annual rates in period 2006–2010. These observations were split into total, corporate and household NPLs. We calculated the average ratio of sectoral NPLs to total NPLs and we applied derived coefficients on NPLs from the rest of sample period in order to generate time series of both corporate and household NPLs from Q1 2000 to Q2 2010. Then, we calculated sectoral NPL ratios by comparing sectoral NPLs to corresponding sector's total loans.

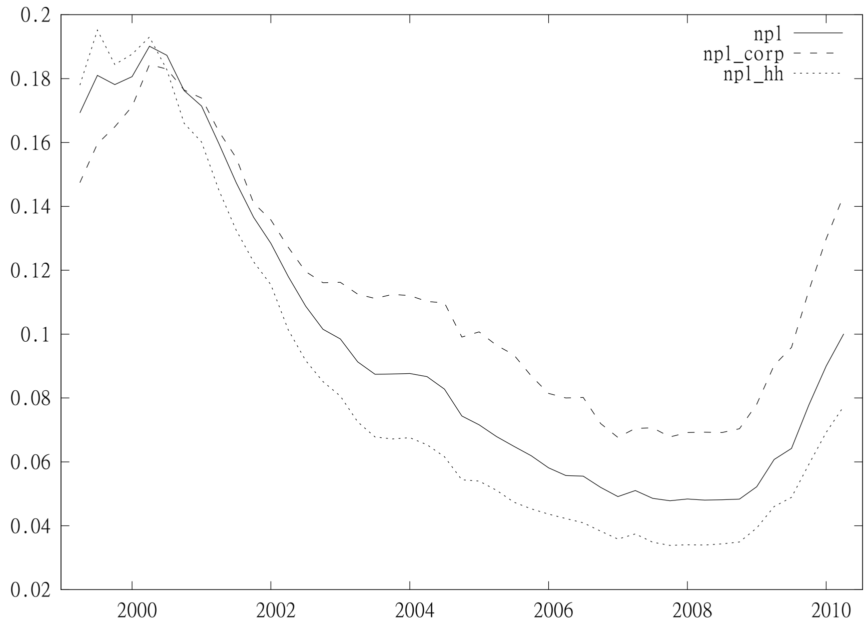
Figure 4.1 shows development of total and sectoral default rates over the sample period. NPL ratio (default rate) reaches relatively elevated values of around 18% during the years 2000 and 2001. According to our estimations, in the same period households show higher rates than companies. This differs from commonly observed pattern. Demonstrated values suggest that at the beginning of the 21st century, even though the corporate loans accounted for the major part of total loans, the repayment discipline of Croatian households might have been lower than that of companies. In the following year, however, the trend has changed and corporate default rate outranked household rate. Accordingly, default rates began to descend and they reached their minimum

[12]Accordingly, CPI was employed in calculations of real values of particular macroeconomic variables such as effective exchange rate or interest rates.

[13]Interest rate spread is defined as a difference between interest rates on total loans and on total deposits.

[14]The calculation of unemployment rate is based on definition of unemployment rate provided by International Labour Organization (ILO) (unemployment rate is number of unemployed persons as a percentage of labour force, see http://www.ilo.org). For period 1999–2001 only annual unemployment rates were available. Assuming equally distributed inflow of labour force and unemployed over the year, we linearly interpolated annual data in order to obtain quarterly growths.

Figure 4.1: Total NPL ratio and estimated NPL ratios for corporate and household sectors in Croatia.



Source: Author's computations. Variables *npl*, *npl_corp* and *npl_hh* represent total NPL ratio, corporate NPL ratio and household NPL ratio, respectively.

in year 2008 (default rates of 6.8% for corporations and 3.4% for households). All rates jumped up when the financial crisis emerged in late 2008. Their increasing tendency is noticeable until the end of sample period with 2010 values of 14% and 8% for corporations and households, respectively.

4.2.2 Serbia

In case of Serbia, we used National Bank of Serbia (NBS) on–line database to generate macroeconomic data, except for GDP growth rate in the EU 15.[15] In line with existing literature, we consider following variables for corporate sector: 1) real GDP growth rate in Serbia and in the EU 15 as it is Serbian main trading partner[16], 2) Industrial Producer Prices (PPI) growth rate as an indicator of inflation[17], 3) real industrial production growth rate, 4) growth rate of nominal RSD/USD and RSD/EUR exchange rates, 5) growth rate of

[15] Available at: http://www.nbs.rs

[16] According to NBS's reported data, during the period 1997–2010 56.9% of goods were imported from the EU and 54.2% of goods were exported to the EU, on average.

[17] It is more convenient to use CPI as a measure of inflation. Due to lack of data on CPI for periods before 2007 we utilise PPI. Moreover, where practicable, PPI was used to derive real values of other macro indicators.

nominal and real effective exchange rates[18], and 6) growth rate of nominal and real lending interest rates. All rates were obtained on the basis of quarter to corresponding quarter of previous year.

For household sector model, we use these indicators: 1) real GDP growth rate in Serbia, 2) growth rate of PPI, 3) growth rate of unemployment rate[19], 4) growth rate of nominal RSD/USD and RSD/EUR exchange rates, 5) growth rate of nominal and real effective exchange rates, and 6) growth rate of nominal and real lending interest rates[20]. Due to restrictions in NPL's time series, the models for corporate and household sectors has been estimated for period Q3 2004–Q3 2010.

In case of Serbia, some modifications of dependent variable were done in order to obtain sufficiently long time series to run the model. Quarterly values of NPLs were available for the period from 2008 Q3 to 2010 Q3 (9 observations). In order to extend time series, we analysed relationship between NPLs and classified assets in categories C+D+E (CDEs), as we assumed the former to be subcategory of latter.[21] After the adjustment of CDEs for structural break, which was caused by methodological change in classifying items and provisions in 2006, and after multiplying CDEs with the coefficient derived from observed relationship between CDEs and NPLs, we arrived at estimated NPLs for the period 2004 Q3–2008 Q2. The analysis added another 16 observations to our data set, which now contains 25 observations for Serbian corporate and household credit risk models.

Next, we divided total quarterly NPLs into corporate and household NPLs. The NBS has been reported sectoral NPLs since the third quarter of 2008. For previous periods, division has been done based on coefficients derived from rela-

[18] For years 2003 and 2004 annual data on exchange rates were only available. We multiplied these numbers with coefficients indicating relationships between exchange rates in available periods and we obtained quarterly estimations for 2003–2004.

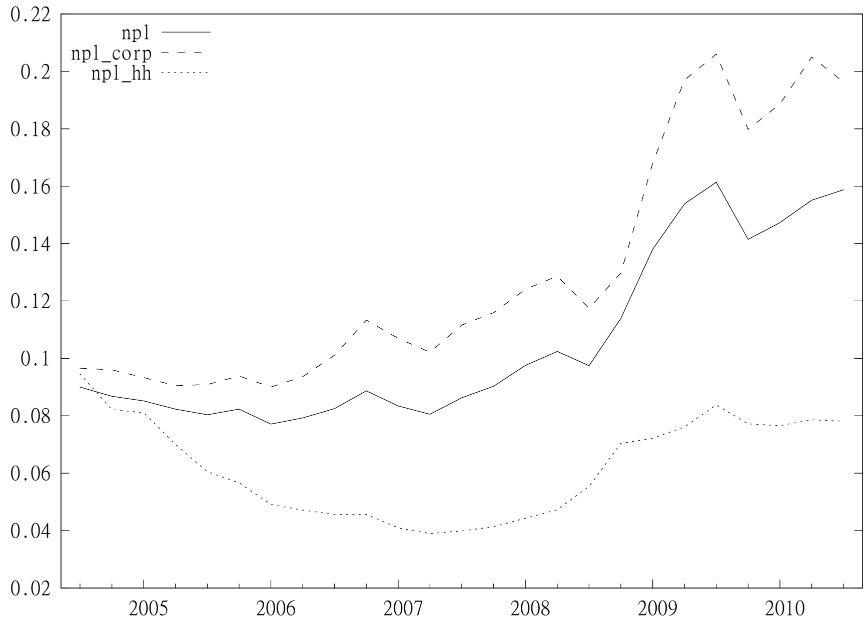
[19] For years 2003 and 2004 the number of unemployed was available only on annual basis. Therefore, we investigated the change in number of unemployed during the year on available data and we applied gained coefficients on data from years 2003 and 2004. For the calculation of unemployment rate the number of unemployed was divided by number of active population over 15 years, which has been available in Serbian Statistical Office database (Available at: http://webrzs.stat.gov.rs). The number of active population was available only on annual basis, hence we assumed it to be constant during a particular year in order to arrive at unemployment rate.

[20] It is possible to distinguish lending interest rates for households and corporates and to apply particular rate to corresponding debtor. Due to the lack of sufficiently long time series on separate lending rates we do not consider this approach in the case of Serbia.

[21] NBS's definitions of these variables indicate that by subtracting category C from CDEs we can arrive at NPLs values. For exact definitions of NPLs and categories of classified assets we refer to NBS (2011).

tionship between total NPLs and sectoral NPLs in the sample period. Finally, we divided sectoral NPLs by corresponding total loans, and we obtained household and corporate NPL ratios. Figure 4.2 shows the development of total and sectoral NPL ratios over time. NPL ratio, which represents the default rate, remains almost stable during the period from 2004 to mid–2007, demonstrating slightly increasing tendency for corporate loans and a little decreasing trend for household loans. From mid–2007 all indicators increase, especially noticeable is a sharp increase in corporate default rate from mid–2008 to mid–2009. Corresponding period reflects the appearance of crisis in Serbia.

Figure 4.2: Total NPL ratio and estimated NPL ratios for corporate and household sectors in Serbia.



Source: Author's computations. Variables *npl*, *npl_corp* and *npl_hh* represent total NPL ratio, corporate NPL ratio and household NPL ratio, respectively.

In comparable period, Serbian default rates demonstrate similar path as those of Croatia. Low values of default rate at the middle of decade are replaced by the increase after the 2008 turmoil. Serbian default rates are characterised by higher volatility, as well as higher absolute values than those of Croatia (see Figure 4.2). In case of Croatia, all rates (total, corporate sector and household sector) show more or less similar trends, mainly at the end of period. On the other hand, Serbian rates differ, particularly household default rate during the whole sample period. Relatively low default rates for households compared to those of corporates in case of Serbia could be caused by lower demand for household lending or higher requirements for credit granting. Thus, debtors might be of higher repayment discipline.[22] However, relative to household default rates in other countries, Serbian ones are elevated. Higher repayment discipline of households is demonstrated also in Croatia. The share of household loans and corporate loans to total loans is almost the same (slightly below 50% for recent years). Yet, household rates are by 3% lower than those of corporates, on average (default rates of 8% and 11% for households and corporates, respectively).[23]

4.3 Credit Risk Model for Corporate Sector

In whole study we use econometric software Gretl 1.9.1csv. Macroeconomic indicators for Croatia and Serbia were chosen based on existing literature, data availability, availability of data projections and expert judgement, with the aim to consider data that would explain default rates in a meaningful fashion. We consider also time lags of variables in order to describe the model realistically. The matrix of correlation coefficients for each country has been derived to identify possible correlations between explanatory variables. We presumed that there could be correlations primarily between variables concerning interest rates and exchange rates, which have been proved. Significant correlation between industrial production growth rate and GDP growth rate in Serbia and between GDP growth rate in the EU 15 and growth rates of industrial production and nominal and real effective exchange rates appeared (see Table B.1 in Appendix B). In case of Croatia we found the correlation between Croatian GDP growth rate and the EU 15's GDP growth rate, rate of growth of unemployment rate, real interest rate growth rate (total and household lending) and disposable income growth rate (see Table B.2 and B.3 in Appendix B). We aimed not to include correlated variables together in the model.[24]

[22]Household loans represent 28.5% of all loans on average, whereas corporate loans account for 62.5% of loans in the period 2004–2010.

[23]Note that provided default rates can slightly differ from the actual ones, especially at the beginning of period. The difference can be caused by modifications that were carried out in order to obtain longer time series.

[24]The correlation coefficient was above 0.5 in absolute values also for (1) GDP growth rates in the EU 15 and Serbia, (2) GDP growth rate and rate of growth of unemployment rate and real interest rate in Croatia, and (3) growth rates of unemployment rate and HRK/USD exchange rate in Croatia. Nevertheless, the small break of bounds, which were set by expert judgement in interval [-0.5,0.5], and the relative importance of variables encouraged us to use them together in the model. Alternatively, we test all models for collinearity, which was not proved in none of them.

Next, all variables were tested for stationarity. Despite of relatively short time series the results of tests suggest that we should not deny the stationarity of variables.[25] The regression analysis was performed using the Ordinary Least Squares (OLS) method that was applied to default rate (NPL ratio) expressed in logistic form.[26] We started with univariate regression analysis to select significant explanatory variables and their lags, then we applied step–wise regression to detect the model that explains corporate default rate most properly. Following Jakubík & Schmieder (2008) and being aware of relatively short sample period we included as few explanatory variables as possible in the final model. Accordingly, we control the model for possible structural breaks using the QLR test and additional Chow's and CUSUM tests. Following subsections provide specific credit risk models for Croatia and Serbia.

4.3.1 Croatia

The macroeconomic credit risk model that appeared to explain default rate movements of Croatian corporate sector in the best possible way looks as follows:

$$\begin{aligned} ln\left(\frac{npl_{corp,t}}{1-npl_{corp,t}}\right) &= \alpha + \beta_1 g\_hr_{t-4} + \beta_2 r_{t-4} + \beta_3 \pi_{t-3} \\ &\quad + \beta_4 er\_usd_{t-2} + \beta_5 dum1_t + \beta_6 dum2_t \end{aligned} \tag{4.4}$$

where $npl_{corp,t}$ is default rate defined as a portion of corporate NPLs to total corporate loans in time t, g_hr denotes GDP growth rate in Croatia, r is growth rate of real interest rate, π is inflation measured by CPI, er_usd stands for growth rate of HRK/USD exchange rate and $dum1$ and $dum2$ are dummy variables that adjust the model for structural breaks, which have been detected and proved by QLR and Chow's tests. Value of $dum1$ is 1 for period until the fourth quarter of 2004 and 0 afterwards. Accordingly, value of $dum2$ is 1 until Q3 2005 and 0 afterwards (see Figure B.1 in Appendix B). Time lags are also indicated. Structural breaks could be caused by mergers of three big banks with three medium–size banks in 2004.[27]. Next, on January 1, 2004 new regulations that introduced new balance–sheet items (i.e. derivative financial assets

[25] KPSS test's null hypothesis that variables are stationary was not denied.

[26] For the control of assumptions of OLS method, see Table B.4 in Appendix B.

[27] Mergers: Privredna banka Zagreb with Riadria banka, Zagrebačka banka with Varaždinska banka, and Nova banka with Dubrovačka banka. Moreover, the Croatian Na-

and liabilities and other financial liabilities held for trading) came into force as a part of harmonisation process with the EU directives[28] and regulations of Basel Committee on Banking Supervision (BCBS) and International Accounting Standards (IAS). In 2005, two new banking groups were established as a result of changes in ownership structure of banks operating in Croatia. Also, during 2005, the CNB was constantly increasing allocated reserve and marginal reserve requirements.[29]

Table 4.1: Corporate sector credit risk model for Croatia.

Variable	Lag	Coeff. value	Std. error	P–value
$constant(\alpha)$	0	-2.4229	0.0516796	2.38e-030
$g\_hr(\beta_1)$	-4	-3.6435	0.688311	9.26e-06
$r(\beta_2)$	-4	0.0779	0.0241417	0.0030
$\pi(\beta_3)$	-3	3.5724	1.04595	0.0018
$er\_usd(\beta_4)$	-2	1.0648	0.155056	1.07e-07
$dum1(\beta_5)$	0	0.2440	0.0504319	3.41e-05
$dum2(\beta_6)$	0	0.3347	0.0515974	3.09e-07
R–squared:	0.944061	Adjusted R–squared:		0.933234
Rho:	0.043723	Durbin–Watson:		1.850616

Source: Author's computations.

The results from regression are summarised in Table 4.1.[30] According to our results, the most significant variables that explain corporate sector default rate in Croatia are real domestic GDP growth rate, growth rate of real interest rate, inflation and growth rate of nominal exchange rate of Croatian kuna (HRK) against US dollar (USD). All variables are significant at 1 % significance level. There was a noticeable improvement in performance of the model when we added dummy variables.[31]

Apart from real domestic GDP growth rate all coefficients of explanatory variables have positive signs that indicate that the higher the value of variable

tional Bank (CNB) did not revoke bank license for Primus banka d.d., which, therefore, started the closing procedure (CNB 2005a).

[28]Stabilisation and Association Agreement with the EU came into force in February 2005.

[29]Marginal reserve requirement rate increased by 16%, kuna reserve requirement rate by 10% and portion of foreign currency reserve requirement allocated in kuna by 8% in the first half of 2005 (see CNB 2005b, p. 22).

[30]All values refer to dependent variable defined in logistic form which, however, does not change the rule of proportion. In order to derive at original default rate, we need to calculate Equation 4.4 using regression coefficients, with respect to $npl_{corp,t}$. The same rule is valid for all regressions in this chapter.

[31]As is the case of all models in this chapter.

the higher the default rate. Empirically, increasing GDP affects positively demand for goods that companies produce, which in turn increases their profits and creditworthiness. Positive impact of GDP growth on debt repayment was confirmed by our model. The four–quarter lag indicates a delay in corporations' response to changes in economic conditions, which could be caused by, for example, fixed contracts with their business partners. The positive impact of increasing interest rate on default rate is also intuitive, as higher interest rates increase firms' costs of loans, and that can cause problems in their repayment.

Figure 4.3: Actual and estimated corporate sector default rate in Croatia.

Source: Author's computations.

Coefficients for inflation and growth rate of HRK/USD exchange rate have positive signs. The positive effect of inflation and depreciation of domestic currency on default rate can be in contrast with prevailing expectations. As an explanation we should note that inflation can induce default rate to grow if increasing price level forces companies to spend more money on other commodities because they become more expensive. Thus, corporations have less resource to repay the debt, even though the debt becomes cheaper. Also, Baboušek & Jančar (2005) in their simulations of the quality of aggregate loan portfolio in response to macro shocks reject the hypothesis that inflation helps to improve debtors' creditworthiness. The impact of depreciation of domestic currency on default rate depends on position of exporters and importers in economy. The positive impact of depreciation on default rate can suggest that there are more importers in economy, for whom depreciation increases costs of goods that are imported and thus causes problems with debt repayment. In fact, Croatian trade balance has been negative for the whole period 1999–2009.[32]

The performance of estimated model is shown in Figure 4.3.[33] Default rate is measured by NPL ratio. At the beginning of period there was a relatively high level of default rate, exceeding 18% in the mid–2000. However, default rate was then falling rapidly until 2007, when it reached the level of 7%. International financial crisis negatively affected Croatia in 2008. Corporate sector responded by a steep increase in corporate default rate. In Q2 2010, default rate was more than 14%. Estimated model follows the actual values relatively well, especially at the end of period, where it demonstrates lower volatility than at the beginning of period.

Table 4.2: Descriptive statistics of explanatory variables in corporate sector credit risk model for Croatia.

Variable	Mean	Std. deviation	Min	Max
g_hr	0.028816	0.03699	-0.069	0.068
r	0.2362	0.90721	-0.76004	4.3877
π	0.028474	0.01606	0.007	0.076
er_usd	-0.039901	0.094945	-0.17118	0.23208

Source: Author's computations.

Descriptive statistics for explanatory variables is provided in Table 4.2 (time period Q1 2001–Q2 2010). Mean values of domestic GDP, real interest rate and inflation indicate growing tendency on average, although, apart from inflation all of them experienced also periods of decrease. The mean value of exchange rate of HRK against USD points out the appreciation on average. The highest volatility can be found in growth rate of interest rates, with standard deviation of more than 90%.

[32]The negative trade balance means that volume of imports exceeds volume of exports. Considering the trade with all countries in the world and in all products, Croatian trade balance in period 1999–2009 was -6 930 million EUR on average (Source: Eurostat database, available at: http://epp.eurostat.ec.europa.eu).

[33]Note that plotted values in Figure 4.3 are original default rate values that were derived back from logistic form used in regression analysis. Descriptive statistics of the model belongs to dependent variable in logistic form. Unless stated otherwise, all figures in this chapter refer to original default rates, whereas models' statistics are based on dependent variable in logistic form.

4.3.2 Serbia

The estimated macroeconomic credit risk model for the Serbian corporate sector is as follows:

$$ln\left(\frac{npl_{corp,t}}{1-npl_{corp,t}}\right) = \alpha + \beta_1 g\_srb_{t-4} + \beta_2 g\_eu_t + \beta_3 er\_eur_{t-1} + \beta_4 dum_t \quad (4.5)$$

where $npl_{corp,t}$ is default rate defined as a portion of corporate's non–performing loans to total corporate's loans in time t, g_srb denotes GDP growth rate in Serbia, g_eu is GDP growth rate in the EU 15, er_eur stands for growth rate of RSD/EUR exchange rate and dum represents dummy variable, which adjust the model for structural break that have been detected and proved by QLR and Chow's tests (see Figure B.2 in Appendix B). The dummy has the value 1 for the period until fourth quarter of 2008 and the value 0 afterwards. Time lags are also indicated. Structural break at the end of 2008 can be caused by large accounting changes that came into force on July 1, 2008, especially changes in computing and recording receivables, liabilities and lending activities.[34] Moreover, year 2008 was in sign of rapid growth in lending activity that was dominated by credits to corporations. Corporate lending rose by 45% over the year whereas household lending increased by 20%. A 20 % increase in household lending in 2008 is in contrast with the end of 2007 when it increased by 54% relative to the end of 2006.

Table 4.3 summarises results from regression analysis of Serbian corporate sector. We found that the most significant variables are real GDP growth of Serbia and the EU 15 and growth of nominal exchange rate of Serbian dinar (RSD) against euro (EUR). All coefficients of explanatory variables have negative signs, the outcome that is in line with assumptions of negative impact of GDP growth and currency depreciation on default rate in small export–oriented country.

Transmission channels between GDP growth and default rate are relatively easy to trail. Increasing GDP stimulates demand for goods that corporations produce and that increases their profits and ability to repay the debt. The probability of default decreases. A similar view is behind the negative impact

[34]Chart of Accounts and Content of Accounts within the Chart of Accounts for Banks, Guidelines on the Obligation and Methodology of Recording, Compiling, Processing and Delivery of Data on the Stock and Structure of Lending, Receivables and Liabilities of Banks, and Rules on the Forms and Content of Items in Financial Statement Forms to be Completed by Banks (see NBS 2008).

Table 4.3: Corporate sector credit risk model for Serbia.

Variable	Lag	Coeff. value	Std. error	P–value
$constant(\alpha)$	0	-1.2588	0.0464869	3.11e-017
$g\_srb(\beta_1)$	-4	-1.2061	0.561145	0.0440
$g\_eu(\beta_2)$	0	-6.0872	1.59602	0.0011
$er\_eur(\beta_3)$	-1	-1.0998	0.241101	0.0002
$dum(\beta_4)$	0	-0.6843	0.0587632	2.31e-010
R–squared:	0.95049	Adjusted R–squared:		0.940587
Rho:	0.004727	Durbin–Watson:		1.916890

Source: Author's computations.

of the EU 15's GDP growth since the major part of Serbian foreign trade is exported to the EU. Different time lags of the two variables and higher coefficient in absolute value for the EU's GDP could be caused by higher sensitivity of exporting firms. It is possible that exports consist mainly of goods that react cyclically to changes in economic conditions (i.e. cars and machinery) and that contracts are fixed on short periods.[35]

The significance of Serbia's relations to the EU is further demonstrated by the third variable, RSD/EUR exchange rate that was more significant than exchange rate of dinar against USD, for example. The negative impact of depreciation of domestic currency on default rate is given by the fact that currency depreciation favours domestic exporters and increases their profits, which in turn helps to decrease their default rates.

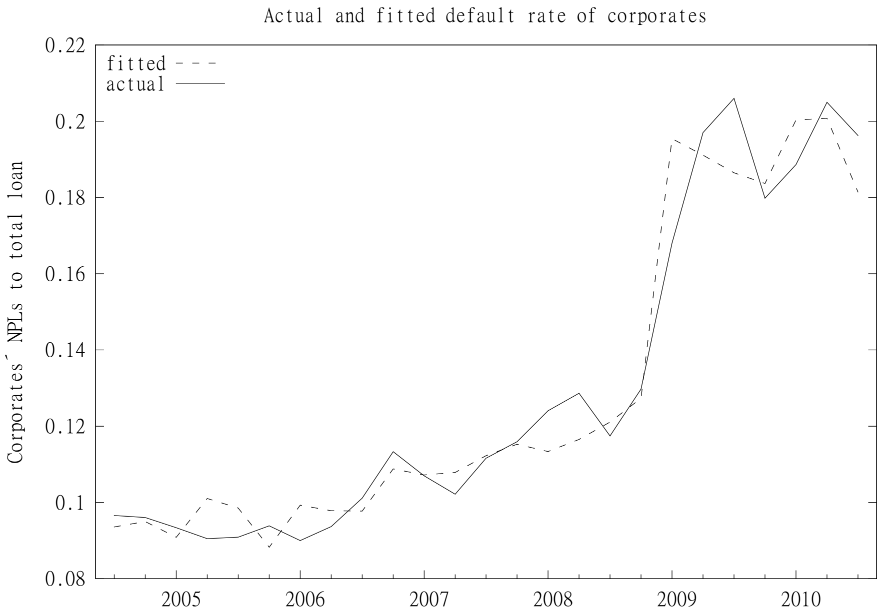
The performance of the model is demonstrated in Figure 4.4. In the first years of period there was a relatively low level of default rate (below 10%) compared to following period that was characterised by a steep increase in default rate in mid–2008 with two peaks in mid–2009 and 2010.[36] The end of period indicates default rates to be around 20%. Values reflect a relatively high portion of "bad" loans and can indicate persistent problems in banking sector in Serbia. The estimated model captures the pattern of actual values more or less properly.

Descriptive statistics for explanatory variables in Serbian credit risk model is provided in Table 4.4 (time period from Q1 2004 to Q3 2010). Mean values of

[35]In fact, machinery, apparatus and transport equipment form the third biggest group of Serbian exports in the last three years, according to NBS's reports.

[36]In comparison to other countries, this value is still very high. Jakubík & Schmieder (2008) analysed corporate sector default rates in the Czech Republic and Germany and their values in 2006 were around 3% and 1.5%, respectively.

Figure 4.4: Actual and estimated corporate sector default rate in Serbia.



Source: Author's computations.

Serbian and European GDPs and exchange rate of dinar against euro show their growing tendency on average, although all of them experienced also periods of decrease. Growth rate of exchange rate experiences the highest volatility with standard deviation of almost 8.5%.

Table 4.4: Descriptive statistics of explanatory variables in corporate sector credit risk model for Serbia.

Variable	Mean	Std. deviation	Min	Max
g_srb	0.044196	0.041625	-0.044797	0.13677
g_eu	0.012993	0.013750	-0.013204	0.029750
er_eur	0.067411	0.084821	-0.0811	0.21429

Source: Author's computations.

When we compare estimated models for Croatia and Serbia we can see some similarities, especially the significance of domestic GDP growth rate and growth rate of exchange rate for both countries. Both Croatia and Serbia have managed floating exchange rate regimes. The dependence of default rate on exchange rates points to small open economies that rely heavily on international trade. Serbia seems to be more dependent on trade with the EU as GDP of the EU and exchange rate of dinar against euro are remaining explanatory variables beside domestic GDP growth. Croatian corporate sector default rate reacts more on exchange rate of kuna against the leading currency in international trade–the US dollar. Remaining explanatory variables are rather domestic – GDP growth, price level and interest rate. Probably due to shorter sample period in case of Serbia, the estimated Croatian model fits better real values and does not experience such volatility as the Serbian one.

In the credit risk model of Croatian and Serbian corporate sectors the macroeconomic factors other than those described above appeared to be non–significant or not appropriate in an economic sense, especially in combination with other factors. We controlled the appropriateness of the model using all tests required for the OLS method, namely normality of residuals, homoscedasticity, autocorrelation of residuals and collinearity of variables. Moreover, we tested the stability of parameters using CUSUM test and the adequateness of model specification using Ramsey's RESET test. None of tests revealed any distresses. Models' coefficients of determination are very high, demonstrating good performance of models in explaining the evolution of default rates. However, given a relatively small sample period especially in case of Serbia, R–squared or adjusted R–squared could be lower if we add more observations. More observations could even change the output or bring more significant variables. What is more, the estimated Serbian NPLs from CDEs for the sample period until mid–2007 and various NBS's and CNB's methodological changes during observed period indicate that we should be conservative when interpreting the model. Thus, we do not see the models as benchmarks that have to be valid in every situation. For our purposes and with available data, however, the models demonstrate good performance and predictive power.

4.4 Credit Risk Model for Household Sector

Similarly to the credit risk model for the corporate sector we verified the basic assumptions as stationarity and correlation between variables before initiating regression analysis for the household sector model. The regression was again performed using the OLS method, applied to the default rate (NPL ratio for the household sector) in logistic form.[37] Firstly, we ran the univariate regression analysis to detect significant variables and their lags. In the step–wise regression the variables interacted and we modified them in order to obtain

[37]For the control of assumptions of OLS method, see Table B.5 in Appendix B.

meaningful model that fits data in the best possible way. Using the QLR test we controlled the model for structural breaks. If a structural break was found, the dummy variable was added to adjust the model for the structural break.

4.4.1 Croatia

The estimated macroeconomic credit risk model for household sector in Croatia is as follows:

$$\begin{aligned} ln\left(\frac{npl_{hh,t}}{1-npl_{hh,t}}\right) &= \alpha + \beta_1 g\_hr_{t-2} + \beta_2 u_{t-3} + \beta_3 \pi_{t-5} \\ &\quad + \beta_4 dum1_t + \beta_5 dum2_t \end{aligned} \tag{4.6}$$

where $npl_{hh,t}$ is default rate defined as a portion of households' non–performing loans to total households' loans in time t, g_hr denotes GDP growth rate in Croatia, u is growth rate of unemployment rate, π stands for inflation measured by CPI and $dum1$ and $dum2$ are dummy variables that adjust the model for structural breaks, which have been detected and proved by QLR and Chow's tests. The value of $dum1$ is 1 for periods prior to Q3 2004 and 0 afterwards. The value of $dum2$ is 1 until Q4 2006 and 0 afterwards (see Figure B.1 in Appendix B). Time lag of every variable is indicated. The first structural break represented by $dum1$ has probably the same grounds as the first structural break in Croatian corporate sector model. The second structural break is not easy to interpret. It could be response to announced privatisation of key state–owned steel, shipbuilding, telecommunication and oil industries, that should have included employee ownership (ESOP – Employee Stock Ownership Plan) as an important part of new ownership structure. New Privatisation Law, however, never came into force, and what is more, the cancellation of the old one was announced in 2009.[38] Another reason for structural break could be the takeover of two banks in Croatia by foreign banks in 2006 and also the introduction of new risk weights (new 75 % risk weight) that led to change in the structure of credit–risk weighted assets.[39]

Table 4.5 shows regression results with macro factors that explain the development of default rate for Croatian households. Domestic GDP growth rate has a negative sign, whereas growth rates of unemployment rate and inflation

[38] BMI (2006) and http://www.tportal.hr/vijesti/hrvatska/9019/Ukida-se-HFP-i-Zakon-o-privatizaciji.html.

[39] CNB (2007).

Table 4.5: Household sector credit risk model for Croatia.

Variable	Lag	Coeff. value	Std. error	P–value
$constant(\alpha)$	0	-3.0912	0.0661304	2.60e-030
$g\_hr(\beta_1)$	-2	-1.8276	0.757563	0.022
$u(\beta_2)$	-3	1.7730	0.208148	1.27e-09
$\pi(\beta_3)$	-5	3.2625	1.39434	0.0259
$dum1(\beta_4)$	0	0.5417	0.0488127	2.51e-012
$dum2(\beta_5)$	0	0.2026	0.0533838	0.0006
R–squared:	0.954021	Adjusted R–squared:		0.946605
Rho:	0.041182	Durbin–Watson:		1.846594

Source: Author's computations.

have positive signs. The negative effect of GDP growth on default rate results from the obvious fact that households benefit from favourable economic conditions. Conversely, increasing unemployment causes default rate to grow as more people lose jobs and their creditworthiness decreases. Inflation again, as in case of Croatian companies, increases default rate probably because people spend more resources on other commodities. A relatively long lags in case of inflation and unemployment suggest that it takes some time until households react to changes in these variables and that they possibly hold some reserves they can use in case of distress.

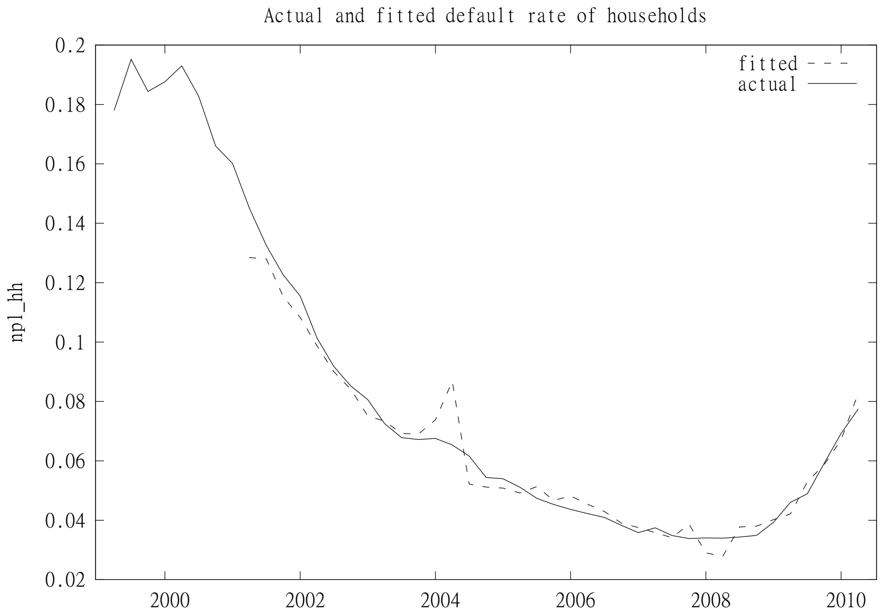
Table 4.6: Descriptive statistics of explanatory variables in household sector credit risk model for Croatia.

Variable	Mean	Std. deviation	Min	Max
g_hr	0.028816	0.03699	-0.069	0.068
u	-0.0315958	0.12523	-0.25688	0.39535
π	0.028474	0.01606	0.007	0.076

Source: Author's computations.

Figure 4.5 demonstrates Croatian household sector default rate for the period from Q1 1999 to Q2 2010. In the first two years of period default rate reached values of almost 20%, which were even higher than in case of corporate sector. However, from 2001 default rate was constantly decreasing. In 2007 it rested on approximately 4 % rate for another two years. Similarly to default rate of firms it started to grow in light of financial crisis in 2009 and it followed increasing path until the end of sample period (see Figure 4.5 and Figure 4.3 in

Figure 4.5: Actual and estimated household sector default rate in Croatia.



Source: Author's computations.

Section 4.3.1 for comparison). In Q2 2010 default rate was around 7.7%. The estimated model catches up the actual values properly, apart from periods of higher volatility around years 2004 and 2008.

Table 4.6 provides descriptive statistics of explanatory variables in household sector credit risk model (time period from Q1 2001 to Q2 2010). Domestic GDP and inflation are the same as in the model of corporate sector and for their discussion we refer to Section 4.3.1. The mean of growth rate of unemployment rate suggests decreasing path over the period with, however, relatively high standard deviation of 12.5%.

4.4.2 Serbia

The final macroeconomic credit risk model for household sector in Serbia is as follows:

$$ln\left(\frac{npl_{hh,t}}{1-npl_{hh,t}}\right) = \alpha + \beta_1 er\_eur_t + \beta_2 u_t + \beta_3 i_{t-3} + \beta_4 \pi_{t-4} + \beta_5 dum_t \quad (4.7)$$

where $npl_{hh,t}$ is default rate defined as a portion of households' non–performing loans to total households' loans in time t, er_eur is RSD/EUR exchange rate growth, u is growth of unemployment rate, i is nominal interest rate growth, π stands for inflation and dum denotes dummy variable that adjusts model for structural break that we found to be in place in mid–2008 (see Figure B.2 in Appendix B), with value of 1 for the period prior to Q3 2008 and with the value of 0 afterwards.[40] The origins of structural break in mid–2008 more likely lay on the same reasons as in case of the corporate sector model (see Section 4.3). Respective time lags are presented in equation.

Table 4.7 sums up regression results and shows the most significant macro factors that explain development of default rate for households. Exchange rate of Serbian dinar against euro, growth of unemployment rate and nominal lending interest rate growth have positive signs, which indicate that they have the positive impact on default rate. The negative sign of inflation suggests the negative impact of this variable on default rate.[41] All coefficients are significant at 1 % level, including dummy variable. There was a noticeable improvement in performance of the model when we added dummy variable.

Table 4.7: Household sector credit risk model for Serbia.

Variable	Lag	Coeff. value	Std. error	P–value
$const(\alpha)$	0	-2.1873	0.0870917	1.83e-015
$er\_eur(\beta_1)$	0	1.1616	0.267025	0.0004
$u(\beta_2)$	0	1.6337	0.218626	6.38e-07
$i(\beta_3)$	-3	0.5167	0.110369	0.0002
$\pi(\beta_4)$	-4	-5.1918	0.740572	1.52e-06
$dum(\beta_5)$	0	-0.1806	0.0365485	0.0001

R–squared:	0.959439	Adjusted R–squared:	0.948172
Rho:	-0.003088	Durbin–Watson:	1.904530

Source: Author's computations.

Positive impact of RSD/EUR exchange rate growth on default rate[42] might be the result of preference for loans denominated in foreign currency (mostly

[40] Chow's test confirmed the presence of structural break at the end of 2008, when the null hypothesis of no structural break was rejected at 1 % confidence level. CUSUM test demonstrated higher parameters' stability in the presence of dummy variable. Additional Chow's tests did not show any other structural breaks.

[41] The positive impact on default rate means that the growth of variable causes default rate to increase. The negative impact appears when the growth of variable leads to decrease in default rate.

[42] That in fact signifies the depreciation of dinar against euro relative to corresponding period in previous year.

in euro) for a part of Serbian households.[43] Non–hedged loans are vulnerable to foreign exchange rate risk, when depreciation of domestic currency makes loans more expensive and their repayment more difficult to accomplish. The consequences of growing unemployment or nominal lending interest rates for household default rate are intuitive. Rising unemployment brings about more people unable to meet their obligations. No time lag between increase in unemployment rate and its effect on default rate can suggest that households do not possess any savings on their disposal, or at least, are not willing to use them for debt repayment if people lose their jobs. Increasing interest rates cause the mark–up of both existing and future loans.[44]

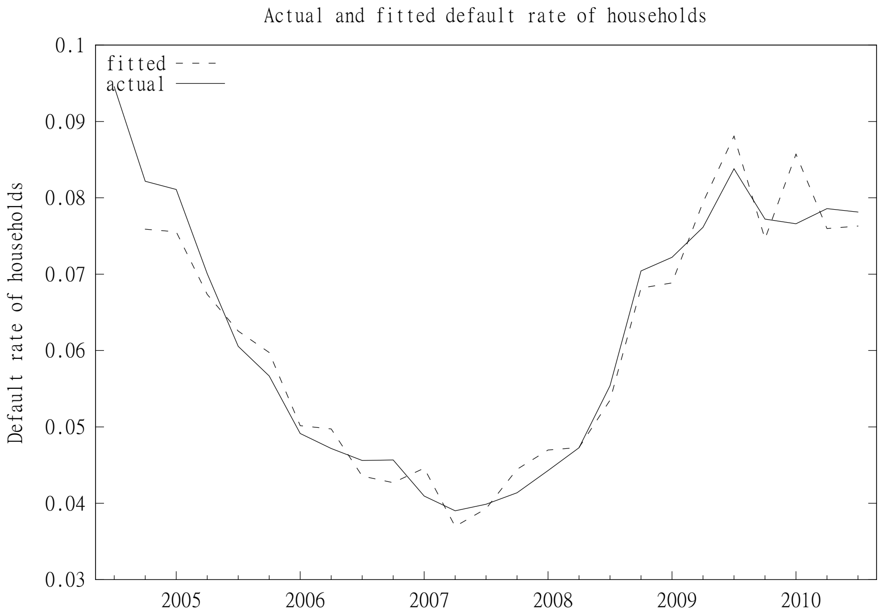
The negative effect of inflation on default rate is demonstrated in deterioration of the real value of debt. Nevertheless, time lag in turning the effect up more likely signals the prevalence of negative effect of inflation on households in form of decreased purchasing power if we assume rigid wages. Households preserve less resource for their credit obligations. When wages adjust to new price level, the purchasing power turns to be at the same level and the positive effect of inflation from debtor's point of view prevails. To sum it up, all signs are in line with our intuitive expectations about the direction of impact of individual explanatory variables.

Other variables such as real GDP growth rate in Serbia, nominal RSD/USD exchange rate growth, nominal and real effective exchange rate growth, and real lending interest rate growth came up to be insignificant in the model described above. However, they might become significant if variables and their lags are chosen differently or if sample period is longer. Yet, given the available dataset of both dependent and explanatory variables, the model described in Table 4.7 shows the best possible performance in estimating household sector default rate, with satisfactory results of all tests required for the OLS estimates, and moreover with good explanatory power that is measured by coefficients of determinacy. Actual and estimated values of default rate are plotted in Figure 4.6. High levels of default rate of almost 10% in 2004 and 2005 were replaced by a sharp decrease until 2007, where default rate reached its minimum of approximately 4%. In the next period the economic situation deteriorated. Following years were in sign of economic recession, with the peak of household default rate in 2009 that was, however, not higher than the rates six years

[43] In the period 2003–2009 the ratio of loans to households denominated in foreign currency to all households' loans was 3.57%, on average.

[44] Assuming that interest rates on loans are not fixed until maturity.

Figure 4.6: Actual and estimated household sector default rate in Serbia.



Source: Author's computations.

earlier. The end of sample period shows default rate reaching almost 8%. The estimated model captures this pattern properly, with exception in the end of 2009, where it shows different trend. After all, it turns to follow the actual pattern at the end of sample period, so that we consider its volatility to decreases continuously.

Table 4.8: Descriptive statistics of explanatory variables in household sector credit risk model for Serbia.

Variable	Mean	Std. deviation	Min	Max
er_eur	0.067411	0.084821	-0.0811	0.21429
u	-0.018288	0.074369	-0.14650	0.093201
i	-0.014288	0.25398	-0.35213	0.62713
π	0.10448	0.036014	0.0490	0.1620

Source: Author's computations.

Descriptive statistics of explanatory variables for the period from Q1 2004 to Q3 2010 is available in Table 4.8. The variable that is volatile the most turns out to be nominal interest rate with standard deviation of 25%. Although all variables show positive as well as negative growth rates, inflation reaches only positive values which indicate that there were no deflationary periods in the sample. Mean values suggest unemployment rate and nominal interest rate to decrease and inflation and exchange rate of dinar against euro to increase, on average.

Estimated models for households both in Croatia and Serbia identify the growth rate of unemployment rate and inflation as significant variables in explaining default rates' movements. In both countries the unemployment increases household's probability of default as working is traditionally the main source of income. Inflation influences countries' default rates in opposite ways, having negative effect on default rate in Serbian model and positive effect in Croatian one. It seems that Serbian households respond to increase in inflation by improving repayment discipline (debt is cheaper), even though if it goes in line with higher prices of other commodities. On the other hand, the case of Croatia suggests that if price level increases, households shift their resources from repaying debt to purchasing commodities that become more expensive, thus default rate increases. Nevertheless, both countries react on inflation with a relatively long delay. In remaining explanatory variables the two countries differ.

Similarly as in corporate credit risk models, household model of Croatia shows better performance and lower volatility probably due to longer sample period. Again, we controlled if all assumptions of the OLS model were fulfilled. All test for normality of residuals, homoscedasticity, autocorrelation of residuals, and collinearity of variables showed no deviation from preliminary assumptions. Moreover, CUSUM test for stability of parameters and Ramsey's RESET test for adequateness of the model were performed. Both models demonstrate a relatively good performance and predictive power. Yet, as in the corporate sector model we should be aware of short sample period and we should not regard the models as benchmarks. As a part of future research it could be appropriate to revise them on longer time horizon.

Chapter 5

Macro Stress Testing

5.1 Scenario Analysis

This section develops two scenarios that project macroeconomic conditions for Croatia and Serbia that will be used in stress testing on individual bank's level. The baseline scenario reflects the most likely evolution of macroeconomic factors in one year horizon starting from the end of 2010 and ending in the fourth quarter of 2011. For stress testing of individual banks the macro conditions in Q4 2011 are relevant. The baseline scenario is formulated in line with forecasts provided by international organisations, such as International Monetary Fund (IMF), or macroeconomic survey companies like Consensus Economics (Consensus Forecasts) and Business Monitor International (BMI).[1] If not available elsewhere, we use forecasts of domestic governmental organisations, usually to support or adjust forecasts from other sources.[2] In one year horizon some variables even need not to be projected due to time lags in the macro credit risk models.

The adverse scenario is set by expert judgement, using observed values of individual variables in the past. Our shock consists of movements in all variables that enter the credit risk model, contrary to some studies that stimulate only one variable per shock.[3] We attempt to determine the shock consistently, that is to utilise maximum movements of variables from overlapping periods. This method is so–called historical simulation stress testing. The adverse sce-

[1]Analogous approach was applied i.e. in Fed's implementation of Supervisory Capital Assessment Program (SCAP), see Board of the Governors of the Federal Reserve System (2009a).

[2]In case the forecasts are not available, another possibility is to employ simple vector autoregressive model (VAR).

[3]Similar approach was used i.e. in Jakubík & Schmieder (2008).

nario is plausible because considered values have been already observed. That brings our hypothetical adverse scenario closer to reality, maybe at the expense of severity of the shock.[4] The scenarios consider two sources of risk: credit risk and market risk (divided into interest rate and exchange rate risks). For each sector the baseline and the adverse scenarios are the same.

5.1.1 Croatia

In this section we develop one year horizon baseline and adverse scenarios for Croatia. For variables that enter the credit risk model developed in Chapter 4 we present projected values according to scenario. For the baseline scenario that should reflect the most likely situation at the end of 2011 we employ projections from BMI Emerging Europe Monitor[5], Consensus Forecasts[6] and actual values from CNB's database[7].

More specifically, the baseline situation might look as follows (Table 5.1): at the end of 2010 Croatia experiences negative GDP growth, which affects default rate of corporations at the end of 2011. During 2011 we expect positive GDP growth that affects positively the creditworthiness of Croatian households at the end of the year. There is a 12 % drop in real interest rate in Q4 2010 relative to the same period a year ago. The drop favours corporate debt repayment. Relatively low inflation of 1.4% in 2010 increases to 3.4% in 2011. According to credit risk model estimated for corporate sector in Chapter 4 higher inflation increases corporate default rate. We expect Croatian kuna to appreciate against US dollar by 10.6% in Q2 2011 relative to corresponding period a year ago that was in the sign of depreciation. The appreciation affects negatively corporate default rate. Unemployment rate continues to rise. Described macro variables enter credit risk models of corporate and household sectors. The results of models are estimated probabilities of default (default rates) that will be further used in computations of credit risk losses on individual bank's level.

[4]On the contrary, we could line up observations and take those ones that belong to 5–10 % bottom quantile. Boss (2002) utilises historically observed maximum movements of macro variables in scenario. In this case, however, the scenario need not to be consistent because variables can demonstrate maximum movements in different periods. Oppositely, Virolainen (2004) sets shock expertly by increasing or decreasing values of variables by certain percentage points.

[5]See BMI (2011).

[6]Consensus Economics (2010a,b).

[7]Namely, we used data from Consensus Forecast to project GDP growth rate and inflation and BMI data for HRK/USD exchange rate. Unemployment rate was adopted from Eurostat database and real interest rate from CNB. Some values were not projected due to their time lag in the model.

Table 5.1: Explanatory variables that enter credit risk models for actual, baseline and adverse scenarios in Croatia.

Corporate sector	Time lag	Actual (%)	Baseline (%)	Adverse (%)
g_hr	-4	-6.9	-0.6	-6.7
r	-4	439	-12	18
π	-3	1.0	3.4	6.4
er_usd	-2	-1.3	-10.6	- 4.0
Household sector	**Time lag**	**Actual (%)**	**Baseline (%)**	**Adverse (%)**
g_hr	-2	-4.6	0.02	-5.7
u	-3	26.8	23.9	36.3
π	-5	3.8	1.4	1.4

Source: Author's computations. Actual scenario refers to Q2 2010, baseline and adverse scenarios to Q4 2011. Variables g_hr, er_usd, u, r and π represent growth rates of Croatian GDP, HRK/USD exchange rate, unemployment rate, real interest rate, and inflation, respectively. Values are showed with respect to time lag in which they appear in the model (for example, Croatian GDP growth rate of -6.9% is the value of Q2 2009 that due to time lag appears in the model that estimates Q2 2010 situation).

Economic conditions regarding market risk at the end of 2011 are described in Table 5.2. For the calculation of bank's interest rate losses the CNB's key interest rate is relevant. CNB has not changed it since 2008 and it was announced that the rate would not change in the first half of 2011. We assume that the rate will rest on 9% until the end of 2011 for baseline scenario. For exchange rate losses we use projected exchange rates of kuna against US dollar and euro from BMI's forecasts. These are 7.01 and 5.27 HRK/EUR and HRK/USD, respectively.[8] The rates reflect appreciation of kuna. The comparison to Q4 2010 situation is provided in the table. Overall baseline scenario suggests that in 2011 Croatia might experience economic recovery.

In adverse scenario we have changed all variables except for inflation in case of households, due to its time lag. Especially, growth rates of GDP and real interest rate demonstrate highly different paths relative to baseline scenario. The adverse scenario reflects the prolongation of crisis from 2008 or, more specifically, its return after a relatively good conditions in 2010. The influence of 2010 values in 2011–estimations via credit risk models causes that the effect of the shock on default rates is noticeable only in the end of 2011. Default rates in adverse scenario show the same trend as in baseline scenario, except for the

[8] Note that conversely to credit risk, in case of market risk there are no time lags.

Table 5.2: Variables that enter market risk computation for actual, baseline and adverse scenarios in Croatia.

	Actual	Baseline	Adverse
i_cnb	9%	9%	11%
Change to actual scenario	–	+0%	+2%
er_eur	7.39	7.01	7.29
Change to actual scenario	–	-0.38	-0.10
er_usd	5.57	5.27	5.00
Change to actual scenario	–	-0.30	-0.57

Source: Author's computations. Actual scenario refers to Q4 2010, baseline and adverse scenarios to Q4 2011. Variables *i_cnb*, *er_eur* and *er_usd* indicate CNB's key interest rate, HRK/EUR and HRK/USD exchange rates. Values of baseline and adverse scenarios will serve as inputs in computations of individual bank's losses from market risk.

end–of–year values. Yet, in two–year horizon the effect of the shock could be fully translated into deterioration of default rates. Specifically, we assume negative domestic GDP growth rate of more than 5% through the whole year, the situation experienced in 2009. We let inflation and unemployment rate to increase, the situation that was observable in some periods of recent crisis in Croatia. We suppose also that CNB perceived increasing inflation and that it aims to fight it by elevating its interest rate. The result is the increase of banks' interest rates. The intervention does not lower inflation until the end of the year, which in our credit risk model would be noticeable in 2012.

For market risk calculation the input variables in adverse scenario are chosen as follows: Assuming CNB's efforts to lower inflation, we increase its base interest rate for 2%. The increase will negatively affect banks' available–for–sale securities in balance sheets. It will affect also interest income that arises from maturity gap between interest sensitive assets and liabilities, however with uncertain impact. For exchange rate risk we assume two main exchange rates, kuna against euro and kuna against US dollar. They are set according to 2009 values. For both cases kuna appreciates relative to Q4 2010 values. The impact of exchange rates on banks' portfolios will depend on net open foreign exchange (FX) position of a bank in particular currency. Credit risk default rates arisen from scenarios are depicted in Figures 5.1 and 5.2 in Section 5.2.1.

5.1.2 Serbia

This section describes the set up of 2011 scenarios for Serbia. For one year baseline estimations of Serbian and EU 15's GDP growth rates and growth rates of unemployment rate and RSD/EUR exchange rate we employed projected data from Consensus Forecasts, IMF World Economic Outlook[9], BMI Emerging Europe Monitor and Centre for Strategic Economic Studies "Vojvodina–CESS".[10] Due to time lags of inflation and growth rate of nominal interest rate in credit risk models we did not forecast these variables.

Table 5.3: Explanatory variables that enter credit risk models for actual, baseline and adverse scenarios in Serbia.

Corporate sector	Time lag	Actual (%)	Baseline (%)	Adverse (%)
g_srb	-4	-2.19	3.30	-4.29
g_eu	0	2.40	1.40	-0.87
er_eur	-1	11.70	-1.01	- 6.04
Household sector	**Time lag**	**Actual (%)**	**Baseline (%)**	**Adverse (%)**
er_eur	0	14.15	-0.38	-1.07
u	0	-0.92	-4.32	4.50
i	-3	-34.95	23.27	60.83
π	-4	5.30	16.20	16.20

Source: Author's computations. Actual scenario refers to Q3 2010, baseline and adverse scenarios to Q4 2011. Variables g_srb, g_eu, er_eur, u, i and π represent growth rates of Serbian and the EU 15's GDPs, RSD/EUR exchange rate, unemployment rate, nominal interest rate, and inflation, respectively. Values are showed with respect to time lag in which they appear in the model (for example, Serbian GDP growth rate of -2.19% is the value of Q3 2009, which due to time lag appear in the model that estimates Q3 2010 situation).

The baseline scenario for the end of 2011 is as follows: at the end of 2011 we expect EU GDP to grow almost 1.4% relative to the same period a year before. That favours Serbian exporters. The corporates in Serbia also benefit from expected 3.3 % growth of domestic GDP at the end of 2010.[11] On the other hand, expected slight appreciation of dinar causes that exported goods are more expensive and can reduce companies' profits. Thus, the overall impact on

[9] Available at: http://www.imf.org.

[10] Specifically, Consensus Forecasts were used for GDP growth rates projections, BMI's data for RSD/EUR exchange rate, and the average of IMF's and Vojvodina–CESS & IHS (2011) data on unemployment rate.

[11] The forecast value of GDP growth for 2011 was placed in the last quarter of 2010 because actual values of Q4 2010 has not been available.

corporate default rate depends on its sensitivity to changes of given variables. For households, the appreciation can help to reduce default rate, as part of households takes loans denominated in euro. Furthermore, the noticeable drop in unemployment rate (by 4.32%) and a 16 % increase in price level at the end of 2010 favour households.[12]

NBS has announced the increase of its key interest rate to 12.5% in order to fight accelerating inflation. This intervention puts NBS in the group of central banks with the highest interest rates. Accordingly, lending interest rate started to grow at the end of 2010, with 23 % higher values in Q1 2011 compared to the same period last year. As a result loans will be more expensive and their repayment might be complicated (see Table 5.3 and 5.4). Contrary to dinar appreciation against euro, we expect dinar to depreciate against US dollar, the projection provided by forecasters from BMI at the end of 2010. The impact of exchange rate changes on banks' portfolios will depend on their net open positions in given currencies.

Table 5.4: Variables that enter market risk computation for actual, baseline and adverse scenarios in Serbia.

	Actual	Baseline	Adverse
i_nbs	11.5%	12.5%	13.5%
Change to actual scenario	–	+1%	+2%
er_eur	105.5	105.1	104.4
Change to actual scenario	–	-0.4	-1.1
er_usd	79.3	82.4	85.5
Change to actual scenario	–	-3.1	-6.2

Source: Author's computations. Actual scenario refers to Q4 2010, baseline and adverse scenarios to Q4 2011. Variables *i_nbs*, *er_eur* and *er_usd* indicate NBS's key interest rate, RSD/EUR and RSD/USD exchange rates. Values of baseline and adverse scenarios will serve as inputs in computations of individual bank's losses from market risk.

The adverse scenario assumes the different path of macro variables that is in case of GDPs, unemployment rate and nominal interest rate markedly different from actual situation. In adverse scenario we suppose GDP growth of EU 15 to run the course of financial crisis (end–2008) value. Also GDP growth in Serbia experiences crisis situation from the beginning of 2009. Both regions demonstrate negative GDP growth, which is in case of Serbia relatively high, with the value of -4.29%, compared to that of EU 15 (-0.87%). We suppose the

[12] Note that inflation makes loans cheaper from debtor's point of view.

raise in unemployment, with unemployment rate growth rate of 4.5% (Q2 2009 value). The efforts of NBS to fight inflation and higher uncertainty during the shock are reflected in a sharp increase in lending interest rate (2008 values). Banks are not willing to provide credits and they require high compensation rate for them. Around 6 % and 1 % appreciations of dinar against euro (2010 values) favour households whose loans are denominated in euro, but negatively affect exporting companies. Inflation remains the same as in baseline scenario due to time lag. Concerning market risk, we assume NBS to raise its key interest rate by 1% more than in baseline scenario. Exchange rates of dinar against euro and US dollar follow the same direction as in baseline case, but the changes are larger (see Table 5.4). In following section we will use the results of scenario analysis to calculate market and credit risks for Croatia and Serbia.

5.2 Credit Risk

In Chapter 3 we discussed risks to which a bank can be exposed. Credit risk is the main risk that banks face due to their role of intermediary between agents with surplus and those with shortage of resources. Granting loans is an unfinished transaction until the debt is fully repaid (Mejstřík *et al.* 2008, p. 253). There always exists the threat that the debtor will not meet its obligations and that the loan or its part will not be repaid, which will cause the loss in banks' accounting books. Revealing its key role in banks' exposures, authors that deal with banking sector stress testing usually model this type of risk (see Boss 2002, Virolainen 2004 or Jakubík & Schmieder 2008).

As discussed in Chapter 3, there are few approaches how to set macro credit risk model. Chapter 4 introduced models for Croatian and Serbian corporate and household sectors that were developed according to approach originated by Wilson (1997a,b). The models estimated sector's default rate according to movements of specific macroeconomic factors. In this section, we will apply the baseline and the adverse scenarios from Section 5.1 to models developed in Chapter 4. The results will be Croatian and Serbian corporate and household sectors' default rates estimated for Q4 2011. Default rates will be used as probabilities of default for calculation of credit risk losses in individual bank's loan books.[13] Expected and unexpected credit risk losses are usually calcu-

[13]For the sake of simplicity we assume individual bank's portfolio to be homogeneous. Accordingly, we can apply default rates estimated on banking sector's level on individual banks. Note that we have developed two different models for country's corporate and household sec-

lated according to Basel II principles (see BCBS 2006). In our study we will assume only expected losses, the method used i.e. in Jakubík & Sutton (2011). Expected credit risk losses can be calculated as follows:

$$credit\ loss_{t+1} = PD_{t+1} \times LGD_t \times EAD_t \tag{5.1}$$

where PD denotes probability of default expressed in terms of default rate, LGD stands for loss given default and EAD is exposure at default in time t. Jakubík & Sutton (2011) suggest to measure EAD as the difference between outstanding loans and NPLs in time t. Loss given default will be set on the level proposed in Basel II under foundation approach for senior claims on corporates, sovereigns and banks with no recognised collateral (45%, BCBS 2006, p. 67) for Croatia. In case of Serbia we will raise this level to 55%, reflecting higher uncertainty in Serbian economic conditions.[14]

5.2.1 Croatia

This subsection analyses possible future development of specific–sector default rates in Croatia. The baseline and the adverse scenarios are employed. We estimate default rates in one year horizon, starting in late 2010 and ending in the last quarter of 2011. We are particularly focused on values of Q4 2011, which will be used as measures of probability of default in individual bank's credit portfolio.

Let us recall regression equations for Croatian corporate and household sector credit risk models elaborated in Chapter 4. Dependent variables – probabilities of default – will be expressed in terms of NPL ratio, previously denoted as npl_corp and npl_hh. From now, we symbolise them as PD_corp and PD_hh[15]:

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tors that provide two different default rates. We will divide bank's portfolio into loans to corporates and loans to consumers in order to distinct loans with different probabilities of default. In calculation of credit risk loss of individual bank the losses from corporate and household loans will be added together.

[14]As of March 2011, Standard & Poor's provide Croatia and Serbia with ratings BBB+ and BB, respectively (ratings available at http:/www.standardnadpoors.com). The rating of Croatia suggests that the economy has adequate capacity to meet financial obligations but also that economy is the subject to adverse economic conditions, whereas Serbian BB rating suggests that economy is less vulnerable to shocks in near–term but it faces ongoing uncertainties to adverse economic conditions.

[15]We are fully aware that the representation of probabilities of default in terms of NPLs ratio is only an approximation that is used due to lack of data on probabilities of default.

$$ln\left(\frac{\widehat{PD}_{corp,t}}{1-\widehat{PD}_{corp,t}}\right) = -2.4229 - 3.6435g\_hr_{t-4} + 0.0779r_{t-4} + 3.5724\pi_{t-3}$$
$$+1.0648er\_usd_{t-2} + 0.2440dum1_t + 0.3347dum2_t + \epsilon_t \quad (5.2)$$

$$ln\left(\frac{\widehat{PD}_{hh,t}}{1-\widehat{PD}_{hh,t}}\right) = -3.0912 - 1.8276g\_hr_{t-2} + 1.7730u_{t-3} + 3.2625\pi_{t-5}$$
$$+0.5417dum1_t + 0.2026dum2_t + \epsilon_t \quad (5.3)$$

where PD_corp_t and PD_hh_t are banking sector's probabilities of default of loans provided to corporates and households, respectively. GDP growth rate in Croatia is denoted by g_hr, r is growth rate of real interest rate, er_usd is growth rate of HRK/USD exchange rate, u is growth rate of unemployment rate, π stands for inflation measured by CPI and $dum1$ and $dum2$ are dummy variables that adjust models for structural breaks that for 2011 have 0 values and thus do not influence the model.

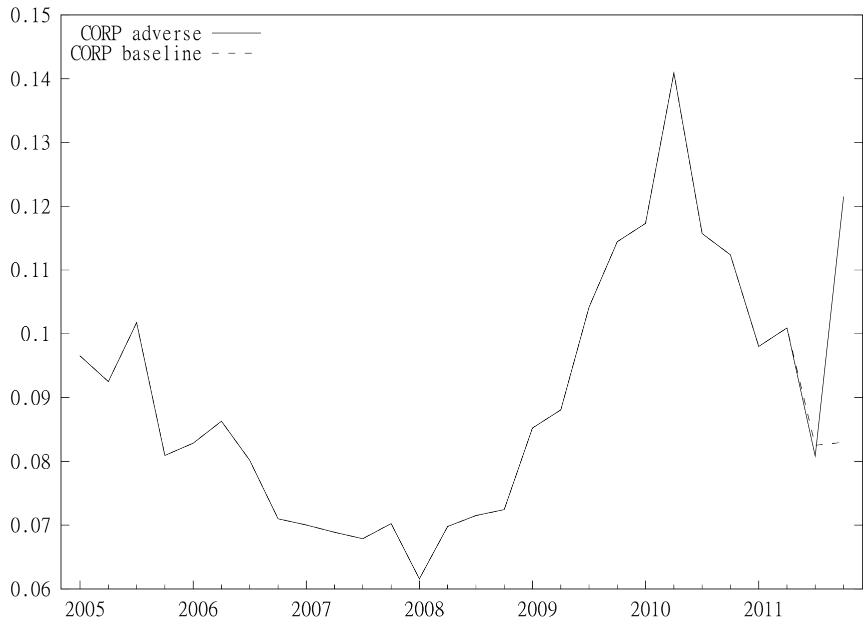
Table 5.5: Credit risk macro stress–testing results for actual, baseline and adverse scenarios in Croatia.

	Actual (%)	Baseline (%)	Adverse (%)
Corporate default rate	14.34	8.30	12.15
Relative to actual scenario	–	-42%	-15%
Household default rate	7.73	6.53	9.13
Relative to actual scenario	–	-15.5%	+18%

Source: Author's computations. Actual scenario refers to Q2 2010 and shows known values, baseline and adverse scenarios refers to Q4 2011.

We put projected values from 2011 scenario analysis in equation (see Section 5.1.1) and we arrive at sector–specific probabilities of default (PDs) for adverse and baseline scenarios in Croatia for the fourth quarter of 2011. Table 5.5 summarises the results and Figures 5.1 and 5.2 provide the graphical presentation of our findings, depicting differences in PD's movements for both scenarios and sectors. The corporate sector probability of default is lower than Q2 2010 value for both scenarios (8.3% and 12.15% for baseline and adverse scenarios in comparison to 14.34 % probability of default in Q2 2010). In the baseline case this reflects the assumption of economic recovery in Croatia in 2011 that should positively influence corporates' creditworthiness. In the adverse scenario the probability of default increases relative to baseline scenario but it does not reach 2010 level. Although we set scenario to reflect the shock in economy, the dependence of macro credit risk model on past values causes that the full reflection of shock will appear later.

Figure 5.1: Baseline and adverse scenarios for corporate sector in Croatia.



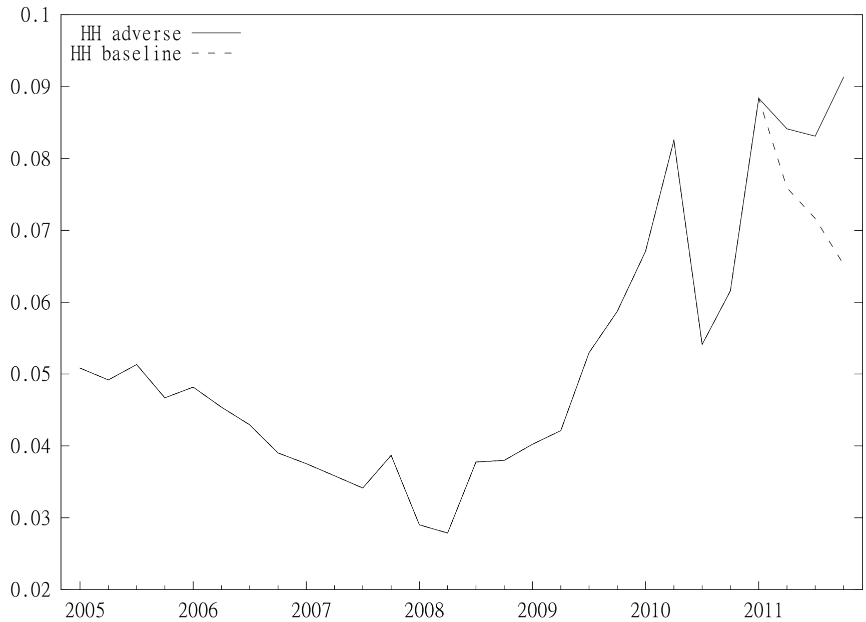
Source: Author's computations.

In case of households, the decrease of probability of default in baseline scenario (-15.5%) is not so noticeable as in case of firms (-42%). However, given the different time lag structure of household's model, the impact of adverse shock translates into higher PD than that which was observed in the past. Namely, the estimated credit risk model for households reacts more swiftly on GDP growth. Households do not profit from appreciation of kuna against US dollar as firms do (see table 5.1). As a result the PD is by 18% higher in case of shock than the PD from Q2 2010.

5.2.2 Serbia

In case of Serbia, the projected sector–specific probability of default in the fourth quarter of 2011 for baseline and adverse scenario is calculated, using

Figure 5.2: Baseline and adverse scenarios for household sector in Croatia.



Source: Author's computations.

estimated macro credit risk models in Chapter 4 and projected macroeconomic variables from scenario analysis at the beginning of this chapter. Regression equations for Serbian corporate and household sector elaborated in Chapter 4 now express sector–specific probabilities of default. They are as follows:

$$ln\left(\frac{\widehat{PD}_{corp,t}}{1-\widehat{PD}_{corp,t}}\right) = -1.2588 - 1.2061g\_srb_{t-4} - 6.0872g\_eu_t \\ -1.0998er\_eur_{t-1} - 0.6843dum_t \tag{5.4}$$

$$ln\left(\frac{\widehat{PD}_{hh,t}}{1-\widehat{PD}_{hh,t}}\right) = -2.1873 + 1.1616er\_eur_t + 1.6337u_t \\ +0.5167i_{t-3} - 5.1918\pi_{t-4} - 0.1806dum_t \tag{5.5}$$

where PD_corp_t and PD_hh_t are banking sector's probabilities of default of loans provided to corporates and households, respectively. GDP growth rate in Serbia and EU 15 are denoted by g_srb and g_eu, respectively. Growth rate of RSD/EUR exchange rate is er_eur, u is growth rate of unemployment rate, i is growth rate of nominal interest rate, π stands for inflation measured by PPI and *dum* is dummy variable that adjust models for structural break, which is zero for 2011.

Table 5.6: Credit risk macro stress–testing results for actual, baseline and adverse scenarios in Serbia.

	Actual (%)	Baseline (%)	Adverse (%)
Corporate default rate	19.63	20.22	25.21
Relative to actual scenario	–	+3%	+28%
Household default rate	7.81	4.78	6.58
Relative to actual scenario	–	-39%	-16%

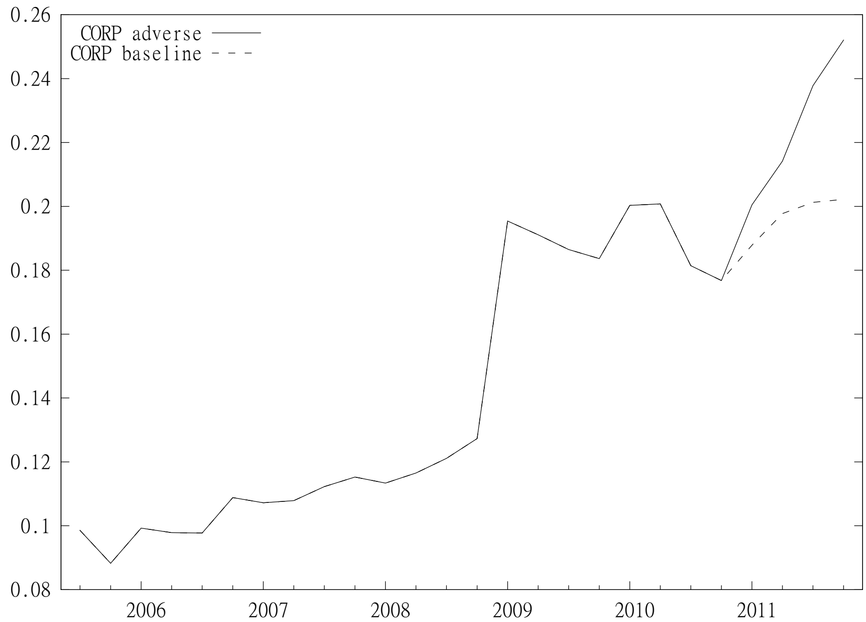
Source: Author's computations. Actual scenario refers to Q3 2010 and shows known values, baseline and adverse scenarios refers to Q4 2011.

We utilise data estimated in scenario analysis for Serbia in Section 5.1 and we obtain corporate and household sector probabilities of default for the end of 2011. Table 5.6 shows the results. Contrary to estimations in Croatia, Serbian corporate sector demonstrates higher PDs both in baseline and adverse scenarios compared to Q3 2011 values. The baseline scenario outcome can signal that firms are more rigid in responses to economic changes in Serbia due to, for example, fixed contracts. Alternatively, the findings might indicate some difficulties in corporate sector's repayment discipline that are still present, regardless the stage of business cycle.[16] Figure 5.3 points out possible stabilisation tendency at the end of considered period for baseline situation.

Household sector's PDs suggest large decrease in baseline situation (-39%) and elevated decrease (-16%) in case of the shock, demonstrating opposite situation than that of firms. Lower PDs under the adverse scenario probably arise from the shape of the model where many variables are expressed in lagged values. Especially, inflation rate of 16% that enters credit risk model of household sector is elevated and favours Serbian households. A relative sensitivity of model to inflation further enhances the effect of inflation (see Equation 5.5). All in all, promising economic conditions at the end of 2010 from households' point of view causes households' PDs to decrease in both scenarios. Still, from the mid–2011 the PDs tend to increase. The question would be what values the PDs would reach in 2012 if unfavourable conditions remained. Figures 5.3 and 5.4 show the evolution of corporate and household default rates for baseline and adverse scenario. The spread between baseline and adverse value at the

[16] Note that the increase in PDs in baseline scenario (+3%) is not very large, whereas in adverse scenario the increase is much sharper (+28%).

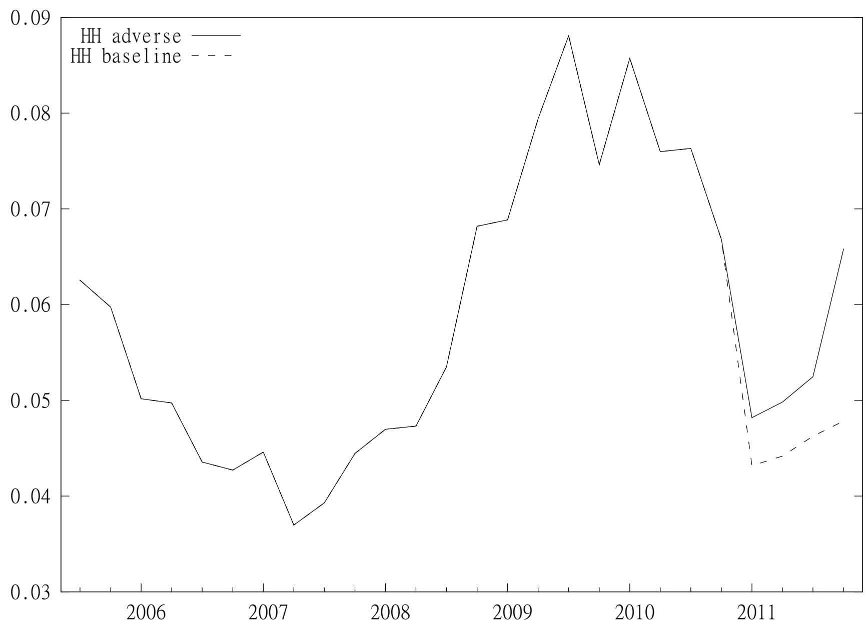
Figure 5.3: Baseline and adverse scenarios for corporate sector in Serbia.



Source: Author's computations.

end of period is wider for firms than for households, with the difference of 5%, compared to around 2% difference for households.

Figure 5.4: Baseline and adverse scenarios for household sector in Serbia.



Source: Author's computations.

5.3 Market Risk

This section provides the insight in computation of market risk. The market risk is the risk of losses in balance sheet and off–balance sheet items caused by changes in market prices. Basel II framework (see BCBS 2006) distinguishes the market risk in: 1) interest rate risk of instruments and equities in trading books, and 2) foreign exchange rate risk and commodities risk. In our study we consider interest rate and exchange rate risks, both of which have direct and indirect impact on banks' loan books. The indirect impact is, however, incorporated in computation of credit risk as it results from the impact of changes in rates on debtors' ability to repay the debt. Hence, we will explicitly assess only the direct impact of these two risks on banks' losses.

5.3.1 Interest Rate Risk

In our study the interest rate risk arouses from marked–to–market bonds held by bank. The increase in interest rate causes the loss from holding these instruments. Apart from original value of bonds we employ also data on duration. Duration is according to FSI Compilation Guide (IMF 2006, paragraphs 3.51–3.56) financial instrument's weighted average term to maturity. In our case duration is approximated by residual maturity, which is provided in individual bank's financial statements.[17]

Interest rate losses are calculated as follows:

$$interest\ rate\ loss_{t+1} = V_t \times D_t \times \Delta ir_{t+1} \tag{5.6}$$

where V denotes original value of the bond, D is duration and Δir is change in interest rate in time t. Čihák (2007) also considers another source of interest rate risk – maturity gap between interest sensitive assets and liabilities. However, we believe it is appropriate to calculate the gain or the loss from maturity gap as part of interest income. The calculation is demonstrated in Section 5.3.3.

[17]This definition is, however, valid only for zero coupon instruments, but due to lack of data and for the sake of simplicity we used it for all instruments. For an exact formula, see FSI Compilation Guide (IMF 2006).

5.3.2 Foreign Exchange Rate Risk

Net open positions in foreign currencies are subjects to foreign exchange rate risk. The FX risk is related to changes in exchange rate of domestic currency against foreign currencies. The net open position in a particular currency is defined as the net spot position plus relevant off–balance sheet derivatives. More specifically, it is sum of value of assets held in foreign currency, minus value of liabilities in that currency, plus value of foreign currency financial derivatives. The calculation of foreign risk loss arising from exchange rate changes in given currency can be written as:

$$foreign\ exchange\ rate\ loss_{t+1} = -NOP_t \times \Delta er_{t+1} \tag{5.7}$$

where NOP denotes net open position in particular currency and Δer stands for change of exchange rate of domestic currency against foreign currency in time t, all in domestic currency units.[18] For more detailed discussion about the calculation of foreign exchange loss, see Čihák (2007, pp. 34–35).

5.3.3 Interest Income Projection

The calculation of direct impact of interest rate change on bank's portfolio when the sensitivities of its assets and liabilities are mismatched can be found in Čihák (2007). We assess the impact of interest rate change on interest income and expenses. The net inflow of interest arises from maturity gap between inflow of interest from holding assets and outflow of interest on liability side of balance sheet. If the maturity gap is positive then the increase in interest rates leads to gains that appear as a part of interest income in income statement. In the next chapter we will add these gains to profit as a part of buffer for potential losses. The interest rate gain is calculated as follows:

$$interest\ rate\ gain_{t+1} = G \times \Delta ir_{t+1} \tag{5.8}$$

where G is cumulative maturity gap between interest sensitive assets and liabilities and Δir is change in interest rate in time t. When the interest rate

[18] Note that we express exchange rate in units of domestic currency per unit of foreign currency throughout the study. Thus, the positive exchange rate change signals the depreciation of domestic currency, which translates into FX gain if the net open position is positive. As we defined dependent variable as foreign exchange rate risk loss, we put the negative sign on the right side of equation. Then the negative loss expresses the gain. Similar approach will be used in the next chapter in order to assess exchange rate risk in individual bank's portfolios.

increases, the positive maturity gap results in gains from interest rate change and vice versa.

In the following chapter we will apply derived equations on individual bank's portfolios in Croatia and Serbia. We will calculate capital adequacy ratio (CAR) for baseline and adverse scenario for individual banks and we will discuss possible policy implications arising from our findings.

Chapter 6

Stress Testing Results

6.1 Overall Banking Sector Environment

For the purpose of stress testing, we used macroeconomic factors from the end of 2010 and we projected their movements in 2011 under two scenarios: baseline and adverse. However, when applying stress tests on individual banks that represent the major part of banking sector in Croatia and Serbia, we approximated banks' financial results of 2010 by data from 2009 because of delay in publishing financial reports. Now, we will discuss the overall banking sector environments in 2009, assuming that they represent 2010 situation.

In Croatia, total banking system assets in 2009 were 379 billion HRK. In our analysis, we have chosen 9 biggest banks, which count for 91.8% of total banking system assets. Regarding the ownership, there were 15 foreign owned banks (91% of total banking system (BS) assets), 17 private domestic banks (5% of total BS assets) and 2 state owned banks (4% of total BS assets).

In Serbia, total banking system assets in 2009 were 2 160 billion RSD. In our analysis, we have chosen 10 biggest banks, which count for 70% of total banking system assets. Regarding the ownership, there were 20 foreign owned banks (74% of total BS assets), 4 private domestic banks (8% of total BS assets) and 10 state owned banks (18% of total BS assets) in Serbia. Selected banks in both countries were of medium or large size.[1] Tables 6.1 and 6.1 provide description of Croatian and Serbian banking systems.

[1] Bank's size is defined in terms of amount of bank's assets relative to total banking system's assets: small bank is a bank with assets' share less than 1% of total assets, medium size bank's assets range from 1% to 5% of total assets, and large bank's assets count for more than 5% of total assets.

Table 6.1: Assets and ownership structure of selected banks in Croatia (in HRK billion).

	Total BS	9 selected banks	Selected banks in % of total BS
Assets	379	348	91.8
Number of FB	15	8	53.3
Assets of FB	344	334	97
Number of PB	17	0	0.00
Assets of PB	19	0	0.00
Number of SB	2	1	50
Assets of SB	16	14	88

Source: Author's computations. Data are from CNB's on–line database, 2009 values. BS is banking system, FB, PB and SB denote foreign–owned, private domestic–owned and state–owned bank.

Table 6.2: Assets and ownership structure of selected banks in Serbia (in RSD billion).

	Total BS	10 selected banks	Selected banks in % of total BS
Assets	2 160	1 512	70.0
Number of FB	20	8	40.0
Assets of FB	1 605	1 184	73.7
Number of PB	4	1	25.0
Assets of PB	177	109	61.7
Number of SB	10	1	10.0
Assets of SB	378	219	58.0

Source: Author's computations. Data are from NBS's Fourth Quarter Report (2009), 2009 values. BS is banking system, FB, PB and SB denote foreign–owned, private domestic–owned and state–owned bank.

6.2 Stress Testing of Individual Banks

In this section we set up equations for calculation of capital adequacy ratio on bank's level. Losses from individual risks are computed in the fashion described in Sections 5.2 and 5.3 in Chapter 5. Capital adequacy ratio (CAR) in time $t+1$ of a bank can be expressed as follows:

$$CAR_{t+1} = \left(\frac{Cap_t + Profit_{t+1} - Credit\_loss_{t+1} - Market\_loss_{t+1}}{RWA_t - \Delta NPL_{t+1}} \right) \quad (6.1)$$

where Cap is regulatory capital. Bank's profit $Profit$ is last 3–year average net income[2] plus net interest rate gain/loss from movements in interest rates, calculated in Equation 5.8 in Chapter 5. Variable $Credit\_loss$ is credit risk loss expressed in Equation 5.1, $Market\_loss$ is market risk loss from movements in interest rate and foreign exchange rate (Equations 5.6 and 5.7), RWA are risk–weighted assets and ΔNPL is inflow of new NPLs with risk weight of 100%.[3] Time t represents end–2010, however, bank data are from the end of 2009, as was discussed above. We implicitly assume, that bank keeps all its profit and does not distribute it among shareholders, which might not be true in reality, especially if the profit is large. Our assumption might lead to high values of CAR. Some banks' results indicate large CAR, i.e. 30–50% (see Tables 6.3 and 6.4). In reality the values could be lower if we assumed that a part of profit was redistributed.

Reduction of RWA by inflow of new NPLs is the consequence of increase in provisioning requirements, which bank has to undertake when NPLs are increasing (see Čihák 2007, p. 29). A common assumption is that the increase in NPLs will be fully subtracted from RWA. In reality, the choice of risk weights depends on information about distribution of NPLs across risk categories of assets. This information is usually not available which is also our case. Thus, in line with Čihák (2007) we assume the risk weight to be 100%. NPLs in time $t+1$ are estimated and used in computation of inflow of new NPLs. According to Jakubík & Sutton (2011), they can be expressed as:

$$\Delta NPL_{t+1} = NPL_{t+1} - NPL_t \quad (6.2)$$

[2] Alternatively, we can use net income of last available year.

[3] The 100 % risk weight for NPLs is assumed i.e. in Čihák (2007).

$$NPL_{t+1} = NPL_t + PD_t \times (Loans_t - NPL_t) - r \times NPL_t \tag{6.3}$$

where PD is probability of default, $Loans$ are current loans in portfolio, and r is average write–off (or sell–out) rate of existing NPLs. As we have estimated default probability for corporate and household sectors separately, we also calculate all relevant parts of CAR formula according to this division and we add results together in final computation. Write–off rates varied extremely across institutions and in time. In 2009, some institutions wrote off only subtle part of its loans. Hence, in 2010, we supposed they might write off greater portion of loans (see Table C.1 in Appendix C). In order to unify conditions for banks and to draw them realistically, we use the average write–off rate of considered banks and we employ it on all banks for the computation of NPLs inflow.

6.3 Results

The stress testing results show bank–by–bank data on 9 largest banks in Croatia and 10 largest banks in Serbia. In terms of assets, our banks cover 92% and 70% of the size of banking sector in Croatia and Serbia, respectively. Although we use real banks' data that are publicly available, we decided not to identify the banks. For the sake of simplicity we call them after the letters in alphabetical order. However, as was already mentioned all data are 2010 data, approximated by real data from 2009.

Before we provide the results of stress tests run on individual banks we should discuss some modifications that we have done due to data limitations. In some banks, not all data that we needed were available. In that case we approximated them or we applied some simplifying assumptions. Particularly, we assumed that the net open positions are all in euro for all banks because we did not have relevant information on all positions that were taken. This assumption does not distort results hardly, as the foreign exchange rates are usually highly correlated (for illustration, see correlation matrices in Appendix B). Similarly, we approximated banks' NPLs by impaired loans, as data on NPLs were mostly not available. Again, there is a high correlation between the two variables, as impaired loans are part of NPLs. Some data were available only on consolidated basis. It relates to one bank in Croatia and three banks in Serbia. However, every bank counts for the major part in group's financial statements, thus we do not assume this approximation to disturb real conditions heavily.

In Croatian Bank D we approximated regulatory capital and risk–weighted assets by averaging other banks' regulatory capital (RWA) and total capital (total assets), dividing these two numbers and multiplying particular bank's total capital (total assets) with obtained coefficient (see Table 6.3). The same was done in Serbia for Banks E and H (see Table 6.4). Next, for Bank F in Croatia data on available–for–sale securities were not provided. Thus, this bank does not show any losses from interest rate movements and as a consequence, its CAR can be overestimated. Similarly, there were no data on net open positions of Bank H and we were not able to compute loss or gain from the change in exchange rate. Finally, Bank G did not report its maturity gap analysis for interest rate risk, so that possible gains or losses were not added to regulatory capital in CAR computation. In case of Serbia, there were no maturity gap data for Bank D.

The results of stress tests applied to selected banks are demonstrated in Table 6.3 for Croatian banking sector and in Table 6.4 for Serbian banks. It should be mentioned that the results reflect the set–up of scenarios and models, therefore they can change easily if we change underlying assumptions. The capital adequacy ratios are provided for initial situation, baseline scenario and adverse scenario. In both countries the regulatory minimum CAR is set by National Banks on the level of 12%. In case of Croatia, we have six large banks which assets count for more than 5% of total banking system assets. There are also three medium–size banks with assets' share between 1% and 5% of total assets in banking system. In initial situation that represents end–2010 situation there is one bank with the CAR lower than regulatory minimum (Bank B). Given that these values are actually from 2009 and that the CNB raised its minimum CAR requirements in April 2010, this bank formally does not show any violation of legal rules. Moreover, the threshold of 12% is elevated relative to other banking sectors including that of the EU (8%). The highest CAR reaches almost 25% (Bank H), the majority of banks has the ratio below 20%. Three banks with the lowest values (two of them are large banks and one is medium–size bank) demonstrate the lowest CAR also under the baseline and adverse scenarios. Banks' CAR under the initial situation, baseline and adverse scenarios are lined up in Figure 6.1.

For Croatia, all banks show positive profits apart from Bank B. Its loss is caused by relatively large loss in the last reported year and by loss from maturity gap between interest sensitive assets and liabilities. Although Bank B profits from market price changes, its CAR deteriorates heavily under the adverse scenario (from 10.13% to 8.39%), falling below the regulatory threshold and reaching almost the EU threshold level. Bank A and Bank G also fall below the threshold under the adverse scenario, but the drop is not so marked. Note that four of nine banks experience gains from interest rate and foreign exchange rate movements under both scenarios, even though under the adverse scenario the gain is lower and also the significance of market risk values relative to credit risk values is smaller.

In case of Serbia, there are six large banks and four banks of medium size. Initial situation demonstrates elevated CAR for all of them, suggesting that Serbian banks are probably very conservative and keep a great capital buffer against potential losses. Under scenarios, one of them demonstrates a drop below the regulatory CAR requirement (Bank F of a large size) in the baseline scenario, and two banks fall below the threshold under the adverse scenario (Bank H and again Bank F, for which the drop is significant). Bank A demonstrates the highest CAR under all scenarios.[4] Bank A's CAR is the highest under the adverse scenario and it is caused by relatively favourable net open FX position. Bank A is the only bank in our sample which share of market risk gain/loss is greater than the share of credit risk loss relative to regulatory capital. Other banks are not oriented to market operations a lot, which is evident from comparison with Croatian banks. The aggregate CAR shows relatively high values under all scenarios. Banks' CAR under the initial situation, baseline and adverse scenarios are lined up in Figure 6.2.

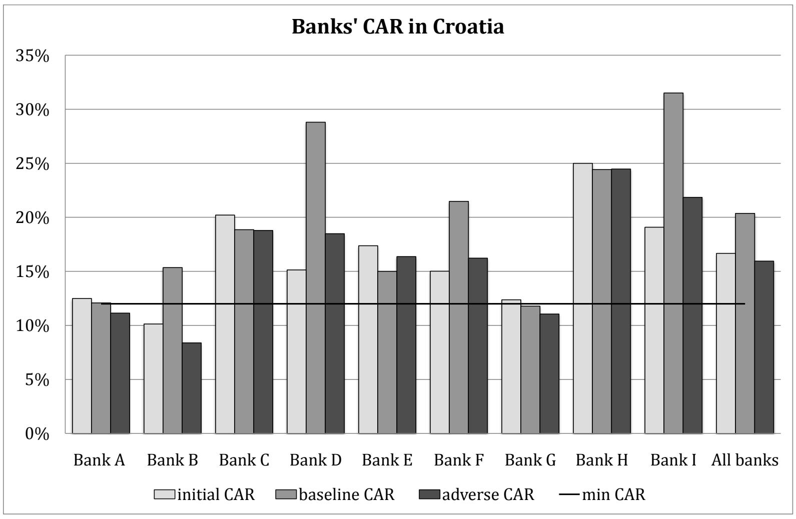
The outcome of movements in market prices for FX positions or bonds in portfolio can significantly vary with scenario that is applied. Contrary to credit risk losses, which are always positive, "good" position in FX or bond market can generate gains to banks, but it is rather an unstable source of profit because it relies heavily on current situation but does not say much about the overall strategy of banks in longer run.

For illustration, Figures C.1, C.2, C.3 and C.4 in Appendix C demonstrate relative significance of credit risk loss, interest rate and foreign exchange rate losses according to country and scenario applied, as a portion of regulatory

[4] Note that we assume that banks keep whole profit and do not redistribute it as dividends. It is probable that bank A with the CAR of 40% would not put aside whole profit to guard against potential risks but would rather redistribute it, at least partially.

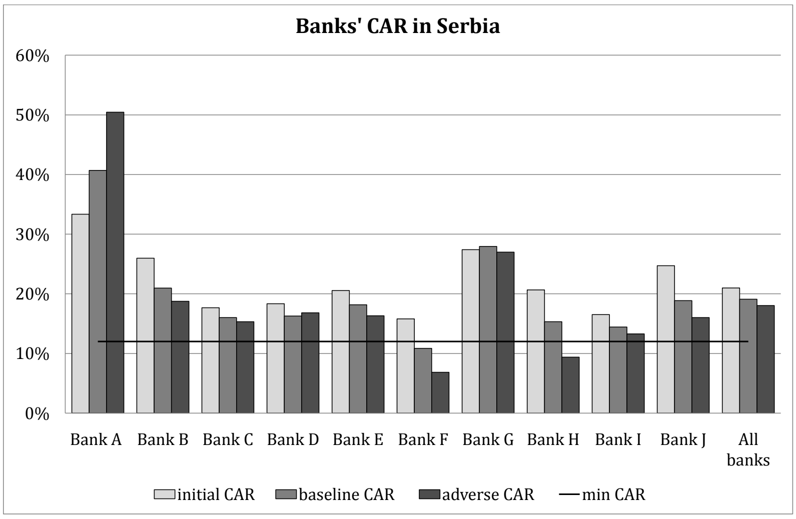
capital. Interest rate risk appears to be slightly significant in all cases but the relative significance of credit risk and foreign exchange rate risk varies.

Figure 6.1: Banks' CAR according to scenario in Croatia.



Source: Author's computations.

Figure 6.2: Banks' CAR according to scenario in Serbia.



Source: Author's computations.

Table 6.3: Stress–testing results for banks in Croatia (in HRK million).

	Bank A*	Bank B	Bank C	Bank D	Bank E	Bank F	Bank G	Bank H	Bank I	All banks
Total assets	50 440	13 981	38 499	12 545	64 519	39 499	27 621	7 640	92 812	347 556
Bank size	L	M	L	M	L	L	L	M	L	
Ownership	FB	SB	FB	FB	FB	FB	FB	FB	FB	
Reg. capital$_t$	5 094	1 012	8 334	1 595**	9 080	4 993	3 050	1752	13 587	48 497
RWA$_t$	40 803	9 983	41 232	10 538**	52 285	33 255	24 664	7 010	71 180	290 950
CAR$_t$(%)	12.48	10.13	20.21	15.14	17.37	15.01	12.37	24.99	19.19	16.67
Baseline										
ΔNPL_{t+1}	2 000	108	1 446	475	1 586	1 703	1 155	251	3 234	11 951
Est. profit$_{t+1}$	705	-106	140	114	986	432	291	59	1 240	3 860
Credit risk loss	1 111	235	919	266	1 357	816	609	160	2 002	7 473
Market risk loss	1	-845	51	-1 456	1 103	-2 168	-38	N/A	-8 587	-11 938
CAR$_{t+1}$(%)	12.08	15.35	18.86	28.81	15.00	21.48	11.78	24.42	31.51	20.37
Adverse										
ΔNPL_{t+1}	3 074	247	1 984	669	2 375	2 259	1 551	363	4 421	18 641
Est. profit$_{t+1}$	826	-111	265	206	1 145	536	291	92	1 366	4 616
Credit risk loss	1 596	298	1 175	354	1 770	1 062	788	212	2 572	10 744
Market risk loss	121	-214	50	-376	289	-561	-1	5	-2 206	-1 058
CAR$_{t+1}$(%)	11.14	8.39	18.79	18.48	16.36	16.22	11.05	24.47	21.85	15.95

Source: Author's computations. L=large bank, M=medium–size bank, S=small bank. FB, PB and SB denote foreign–owned, private domestic–owned and state–owned bank. Initial CAR refers to end–2009, baseline and adverse CAR to end–2011. Negative sign of risk loss signifies gain from the change in rate. From April 1, 2010, the regulatory minimum CAR has been 12%. For initial CAR at the end of 2009 the regulatory minimum was 10%.
* Data for whole Group. ** Data estimations.

Figures 6.3, 6.4, 6.5 and 6.6 demonstrate evolution of banks' aggregate CAR and NPL ratio in Croatia and Serbia under the baseline and the adverse scenarios. The results are shown for three years, where time t denotes the 2010 values. In case of Croatia the aggregate CAR under the baseline scenario increases, whereas under the adverse scenario slightly decreases. In case of Serbia, the CAR decreases under both scenarios. Figures that depict the development of NPL ratio shows that NPL ratios increases rapidly in both countries under both scenarios. The sample period is relatively small but the evolution of variables might suggest that there is a trend of increasing non–performing loans relative to total loans in Croatia and Serbia.

Under the baseline scenario for Croatian banks (Figure C.1 in Appendix C) four banks out of nine demonstrate higher portion of foreign exchange rate risk gains to capital than the portion of credit risk losses. The relative instability of gains or losses from net open FX positions is shown in Figure C.2 (Appendix C), where these gains are much smaller (being 20% of regulatory capital, compared to up to 80% in the baseline scenario) under the adverse scenario, whereas the losses from credit risk raise slightly (from less than 20% to more than 20% of regulatory capital). In case of Serbian banks, as was discussed above, market risk gains/losses are significant only in few banks and just one bank shows higher portion of FX gain than of credit risk loss relative to regulatory capital under the adverse scenario (Bank A).

The stress test results on micro level present the impact of scenarios translated in credit and market risks in terms of CAR. We provide the estimation of overall impact as well as its decomposition into individual risks, calculated as percentages of total regulatory capital. Tables and figures show aggregate impact on total banking systems represented by selected banks.[5] In overall, the stress testing results confirm that banking systems are robust and capable to withstand forecast conditions, as well as plausible economic deterioration. Only minor part of banks shows problems with fulfilling the minimum CAR requirements. On the other hand, some banks' CAR are elevated, indicating that these banks could redistribute some profit and lower the capital buffer that they hold against risks. In the next section we will discuss some policy implications that arise from our findings.

[5]It should be noted that simple addition of aggregate losses from individual risk factors can neglect the cases when risks are concentrated just in some banks which are affected harder than others. For that reason we provide results for each bank and aggregate results are just for illustration.

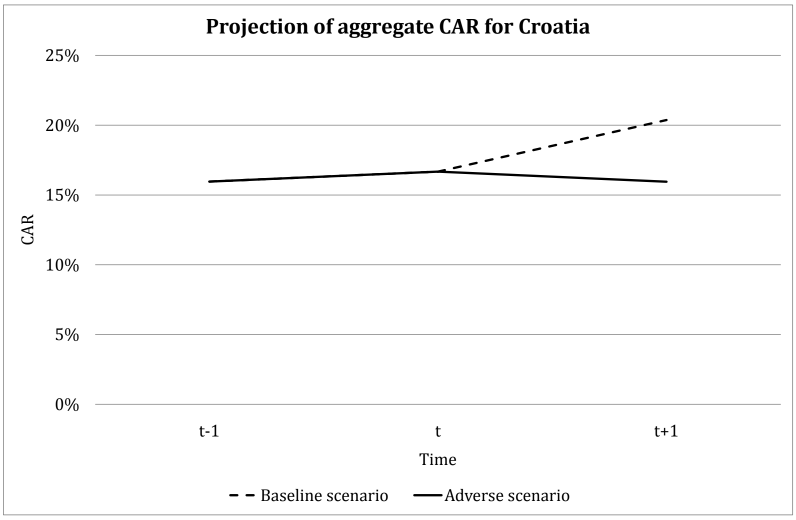
Table 6.4: Stress–testing results for banks in Serbia (in RSD million).

	Bank A	Bank B	Bank C	Bank D	Bank E*	Bank F	Bank G	Bank H*	Bank I	Bank J	All banks
Total assets	109 422	73 650	307 939	146 840	138 923	219 355	193 517	99 711	135 768	87 113	1 512 237
Bank size	M	M	L	L	L	L	L	M	L	M	
Ownership	PB	FB	FB	FB	FB	SB	FB	FB	FB	FB	
Reg. capital$_t$	28632	12 680	46 232	18 792	25 610**	25 096	47 248	16 562**	20 944	13 445	255 240
RWA$_t$	85 850	48 814	261 630	102 510	124 583	158 792	172 374	80 172**	126 785	54 395	1 215 904
CAR$_t$(%)	33.35	25.98	17.67	18.33	20.56	15.80	27.41	20.66	16.52	24.72	20.99
Baseline											
ΔNPL_{t+1}	4 222	2 756	17 219	6 342	11 576	15 011	4 781	8 025	12 893	174	82 901
Est. profit$_{t+1}$	5 441	-608	6 324	2 714	1 710	2 406	5 094	1 857	2 616	1 083	28 637
Credit risk loss	5 329	2 342	13 656	7 326	6 690	10 661	5 049	5 811	7 304	3 914	68 395
Market risk loss	-4 470	78	-249	-1 478	105	1 218	453	1 551	-200	386	-823
CAR$_{t+1}$(%)	40.69	20.95	16.02	16.28	18.16	10.87	27.95	15.33	14.45	18.86	19.09
Adverse											
ΔNPL_{t+1}	6 099	5 479	25 666	10 015	16 451	21153	7 153	10 980	17 308	1 331	121 338
Est. profit$_{t+1}$	5 671	-678	7 628	2 714	1 733	2 158	5 516	2 021	2 700	1 214	30 677
Credit risk loss	6 763	3 661	18 453	10 156	9 424	14 368	6 901	7 699	9 758	5 071	92 571
Market risk loss	-12 687	210	-745	-4 209	272	3 452	1 267	4 384	-672	1 093	-4 142
CAR$_{t+1}$(%)	50.44	18.76	15.32	16.82	16.32	6.85	26.99	9.39	13.30	16.01	18.04

Source: Author's computations. L=large bank, M=medium–size bank, S=small bank. FB, PB and SB denote foreign–owned, private domestic–owned and state–owned bank. Initial CAR refers to end–2009, baseline and adverse CAR to end–2011. Negative sign of risk loss signifies gain from the change in rate. Regulatory minimum CAR is 12%.

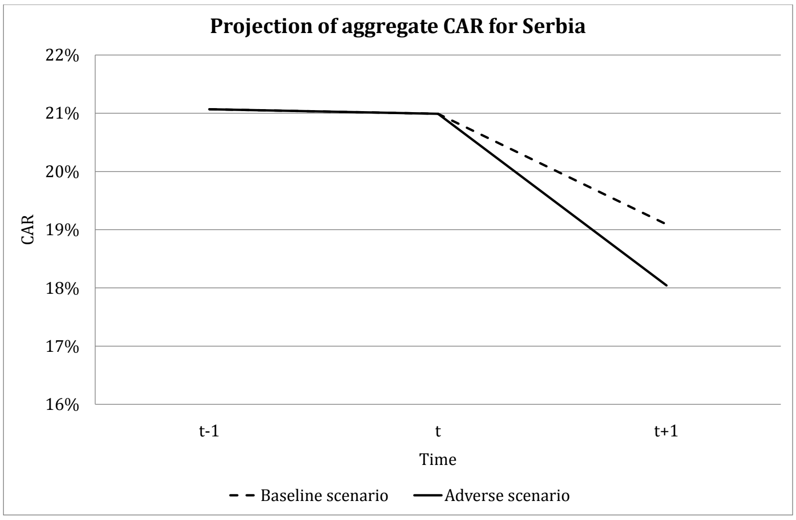
* Data for whole Group. ** Data estimations.

Figure 6.3: Aggregate banks' CAR according to scenario in Croatia.



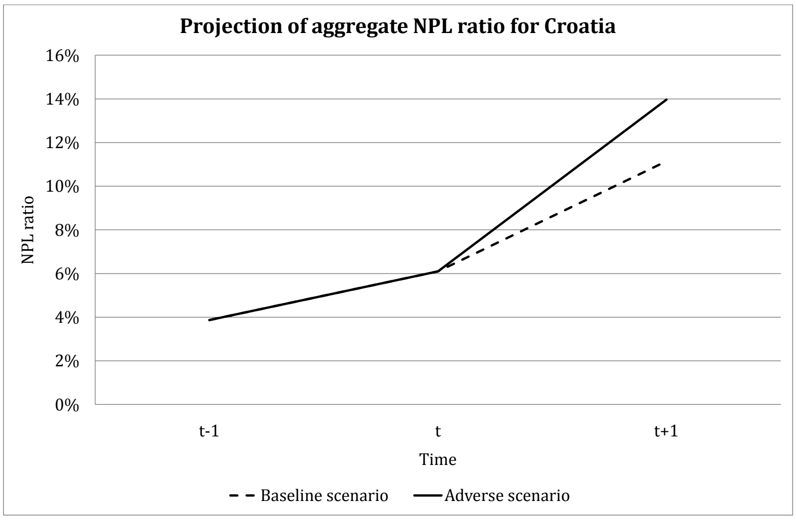
Source: Author's computations.

Figure 6.4: Aggregate banks' CAR according to scenario in Serbia.



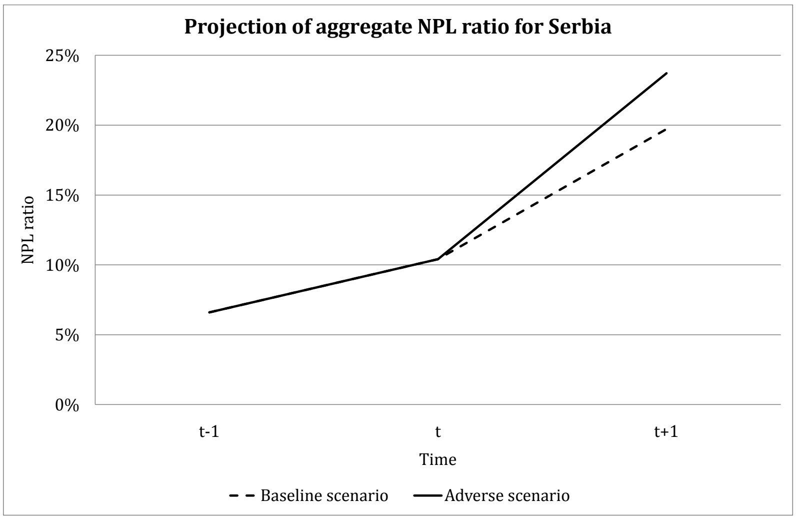
Source: Author's computations.

Figure 6.5: Aggregate banks' NPL ratio according to scenario in Croatia.



Source: Author's computations.

Figure 6.6: Aggregate banks' NPL ratio according to scenario in Serbia.



Source: Author's computations.

6.4 Policy Implications

In this study we aimed to estimate capital adequacy ratios of major banks in Croatian and Serbian banking systems and to compare them to regulatory required CAR, which is one of possibilities how to assess financial stability of banking sector in the country. As Čihák (2007, p. 53) argues, CAR does not capture all potential macro effects from simulated shocks but it can indicate potential fiscal costs of preventing banking failures. At this point it is relevant to consider if the bank in troubles is state–owned, private–owned or foreign–owned. Common opinion suggests that the government will most likely bail–out state–owned banks. But it is not clear whether it will help also private and foreign banks and if not who will then. For banks that lie in the group "too big to fail", the government usually does not have any other option than to provide capital injection. This, however, creates the space for moral hazard in large banks. The size of bank and its ownership structure is particularly important in our study, as the major parts of banking sectors in Croatia and Serbia are controlled by foreign banks.

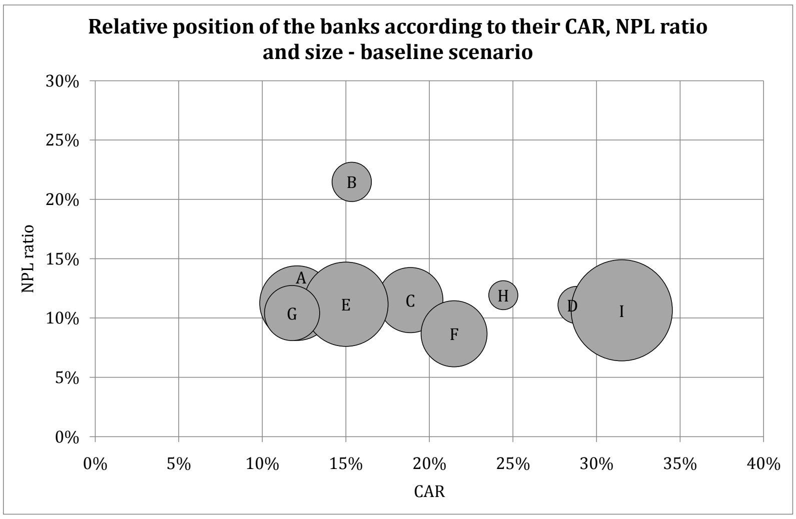
Table 6.5: Injection needed to meet the minimum CAR (in mil. of national currency).

Scenario	Croatia Baseline	Croatia Adverse	Serbia Baseline	Serbia Adverse
Bank A	No need	324.6	No need	No need
Bank B	No need	351.7	No need	No need
Bank C	No need	No need	No need	No need
Bank D	No need	No need	No need	No need
Bank E	No need	No need	No need	No need
Bank F	No need	No need	1 630.6	7 082.4
Bank G	52.0	219.8	No need	No need
Bank H	No need	No need	No need	1 803.4
Bank I	No need	No need	No need	No need
Bank J	–	–	No need	No need
Total	52.0	896.1	1 630.6	8 885.7
Share of GDP_{2009}	0.016%	0.267%	0.060%	0.327%

Source: Author's computations. Currencies: Croatian kuna and Serbian dinar. Share of GDP: total injection needed as a portion of domestic GDP. Data on GDP are in current prices of 2009 because 2010 values were not available. Note that the capital injection is calculated without reflecting any developments that might affect banks' capital or its structure since the end–2009.

Section 6.3 has uncovered the banks that cannot withstand the situations under the baseline and the adverse scenarios. Table 6.5 demonstrates how much additional resources would be necessary to inject in institution (usually in form of capital) in order to bring its CAR up to minimum regulatory level. Under the baseline scenario for both countries, the potential injection would be needed for one bank in total amount representing 0.016% and 0.06% of GDP of Croatia and Serbia, respectively. Under the adverse scenario, however, the amount of capital needed rises by 844 million HRK in case of Croatia and by 7 255 million RSD in Serbia (see Table 6.5). That represents 0.27% of GDP in Croatia and 0.33% of GDP in Serbia. In terms of ownership, the undercapitalised banks in Croatia are two foreign banks and one state–owned. In Serbia undercapitalised banks are one foreign and one state–owned.

Figure 6.7: Bubble chart of NPL ratio, CAR and asset share for baseline scenario in Croatia.

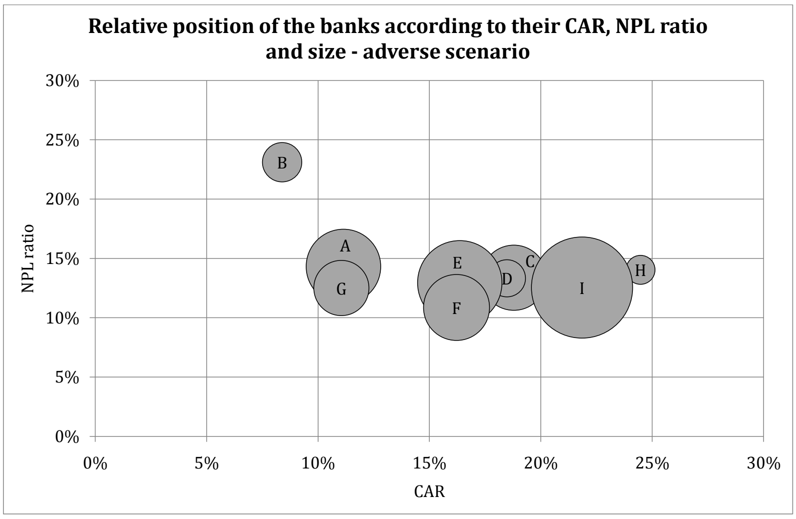


Source: Author's computations.

Figures 6.7, 6.8, 6.9 and 6.10 provide an interesting insight into relative position of all banks according to level of CAR, NPL ratio and bank's size under both scenarios. The NPL ratio represents the portion of NPL in time $t + 1$ to total loans and the bank size is provided in terms of bank's assets to total banking sector assets.

Croatian banks show similar positions in terms of NPL ratio, whereas vary markedly in values of CAR (Figures 6.7 and 6.8). We can distinguish two banks

Figure 6.8: Bubble chart of NPL ratio, CAR and asset share for adverse scenario in Croatia.

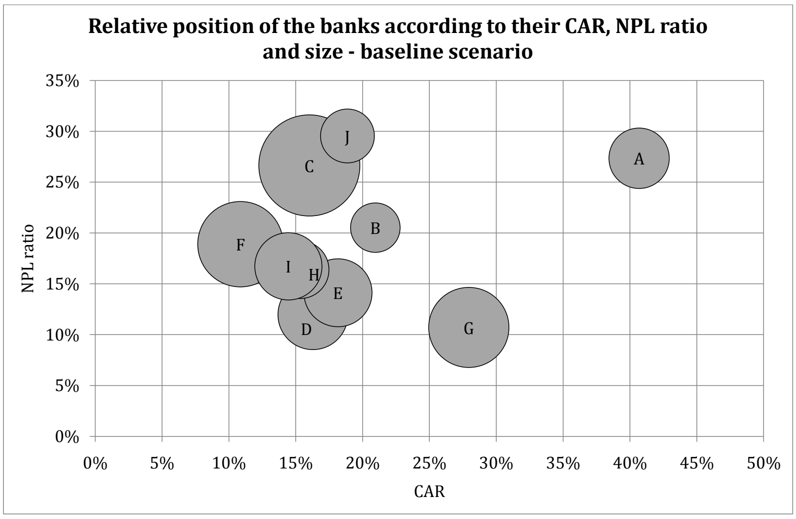


Source: Author's computations.

that are relatively close to the 12 % CAR bound under the baseline scenario and three banks that are below this threshold under the adverse scenario. One of them is significantly large compared to others, the second is of medium size and the third one belongs to the group of smaller banks (Banks A, B and G). Banks A and G are foreign–owned and Bank B is state–owned bank. If we assume these banks to be in threat of bank failure, the government would most probably bail–out the state–owned Bank B, which is the smallest bank in this group. Bank A is quite large compared to others, thus it is not probable that the government would let it to fail. The question might be what would happen with Bank G, which is neither "too big" nor state–owned, and under the adverse scenario it could need the injection of almost 220 million HRK.

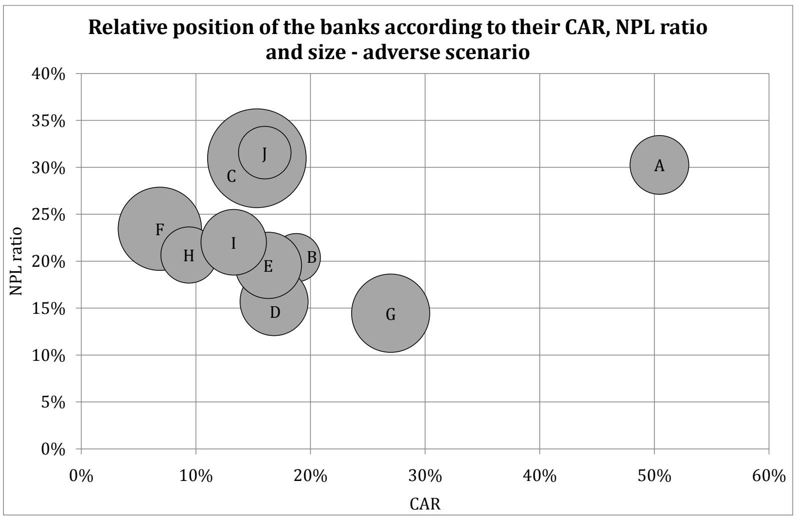
In case of Serbia, the banks are more dispersed in terms of both NPL ratio and CAR (Figures 6.9 and 6.10). Relatively large Bank F lies below the threshold of 12% under both scenarios. Moreover, under the adverse scenario, Bank H also falls below the threshold. As in case of Croatia, the banks below 12 % CAR bound in Serbia are one state–owned and one foreign–owned. In Serbian case, however, larger bank is state–owned, which we believe would be bailout in case of failure. The situation of relatively small foreign–owned Bank H is uncertain. To bail–out both banks under the adverse scenario, the Serbian

Figure 6.9: Bubble chart of NPL ratio, CAR and asset share for baseline scenario in Serbia.



Source: Author's computations.

Figure 6.10: Bubble chart of NPL ratio, CAR and asset share for adverse scenario in Serbia.



Source: Author's computations.

government would need to inject 8 886 million RSD under the adverse scenario. That amount would bring them to 12 % CAR level. Relatively to GDP in 2009, it represents larger share of GDP (0.33%) than in Croatian case (0.27%).

Both scenarios in our study are constructed as “what if” scenarios. Any need for extra capital to meet minimum CAR requirements should not be regard as an obligation or recommendation for the banks. We aimed to assess capital buffer that would help to prevent banking failures if one of scenarios occurred. We do not assess the probability that these scenarios will occur. Regarding the banks that demonstrated enough level of CAR under both scenarios, this exercise can provide market agents with the information about their robustness and capacity to absorb losses, as well as about the financial health of entire economy.

Chapter 7

Revision of Estimated Values

This chapter revises explanatory variables that enter credit risk models developed in Chapter 4. Moreover, it compares default rates of corporates' and households' loans, computed in macro credit risk models using the macro variables, with real values observed in the second half of 2011. By time this thesis was written, we did not have the results of banks' annual reports for 2011 and thus we were not able to compare results from banks' balance sheets with those that we had computed in Chapter 6.[1]

However, at the beginning of 2012 macroeconomic variables that were used in credit risk models were already available. We can revise predicted macro variables presented in Chapter 5 and compare real values of default rates with those that were estimated using macro credit risk models.

7.1 Data for Croatia

Table 7.1 provides real values of macroeconomic variables used in credit risk models for Croatian corporate and household sectors. We see that for inflation and growth rate of Croatian GDP and real interest rate used in credit risk model for corporate sector we used real values in the baseline scenario due to time lags in which these variables appear in the models. In the baseline scenario we expected GDP growth rate to be positive in the second half of 2011 and to change by 2.2% from Q2 2010 value.[2] In fact, the real increase was only about 0.8%. Expected appreciation of kuna against US dollar was in reality slightly higher than in the baseline scenario (13.1% compared to expected 10.6%). Also

[1] Variables like credit risk loss, market risk loss and capital adequacy ratio.
[2] BMI Emerging Europe Monitor forecast.

growth rate of unemployment rate was higher in reality than in the baseline scenario. On the other hand, growth rate of real inflation in Q1 2011 was lower than expected.

Table 7.1: Revised explanatory variables that enter credit risk models for Croatia.

Corporate sector	Time lag	Real value (%)	Baseline (%)	Adverse (%)
g_hr	-4	-0.6	-0.6	-6.7
r	-4	-12	-12	18
π	-3	2.6	3.4	6.4
er_usd	-2	-13.1	-10.6	- 4.0
Household sector	**Time lag**	**Real value (%)**	**Baseline (%)**	**Adverse (%)**
g_hr	-2	0.8	2.2	-5.7
u	-3	25.7	23.9	36.3
π	-5	1.4	1.4	1.4

Source: Author's computations. Real values refer to Q4 2011, baseline and adverse scenarios were computed in Chapter 5. Variables *g_hr*, *er_usd*, *u*, *r* and π represent growth rates of Croatian GDP, HRK/USD exchange rate, unemployment rate, real interest rate, and inflation, respectively. Values are showed with respect to time lag in which they appear in the model (for example, Croatian GDP growth rate of -0.6% is the value of Q4 2010 that due to time lag appears in the model that estimates Q4 2011 situation).

If we put revised macroeconomic variables in the credit risk models now, we can compare results with real Q2 2011 values as well as with baseline and adverse scenario values. Table 7.2 shows that the real portion of non-performing loans to total loans for loans to corporate sector in Q2 2011 is 18.89%. In our credit risk model under both baseline and adverse scenarios the default rates were underestimated. It could be caused by estimated macro variables that turned out to be different from real values. In order to determine whether the relatively huge difference between estimated and real values of default rates were caused by estimated macro variables or by credit risk model set–up, we put real values of macro variables in Equation 5.2 in Chapter 5 that is the result of credit risk model for corporate sector in Croatia. Obtained value of 7.90% is even lower than under original baseline scenario (8.30%). Notice that the adverse value of probability of default is still closer to reality. If the real values of macro variables were closer to adverse scenario values, we would say that the adverse scenario reflect economic development better than the baseline one. Nevertheless, the real economic conditions are closer to baseline scenario. Thus, the similarity in real PD and adverse PD is accidental. Under these findings it seems that the credit risk model for Croatian corporate sector should be revised. Nevertheless, it is difficult for any type of macro model to fit all possible future situations in the economy and because of it the credit risk models are usually subjects to continuous readjustments.

Table 7.2: Credit risk macro stress–testing results for real, revised, baseline and adverse scenarios in Croatia.

Value (%)	Real	Revised	Baseline	Adverse
Corporate default rate	18.89	7.90	8.30	12.15
Relative to real value	–	-58%	-56%	-36%
Household default rate	10.61	6.88	6.53	9.13
Relative to real value	–	-35%	-38%	-14%

Source: Author's computations. Real value refers to Q2 2011 and shows known values, baseline and adverse scenarios estimate Q4 2011 values.

For Croatian household sector we put new values in Equation 5.3. The result suggests that the probability of default is less biased than in case of corporate sector. The Q2 2011 real value of household's probability of default is 10.61%. Both baseline and adverse values of household's probability of default are lower, but the adverse value is closer to reality. If the real values of macro variables were closer to adverse scenario values, we would say that the adverse scenario reflect economic development better than the baseline one. Yet, the real macro values are closer to baseline scenario. Thus, the similarity in real probability of default and adverse probability of default is accidental. Moreover, the revised probability of default is still by 38% lower than real one, which brings the same conclusion as in case of corporates; that is that the credit risk model should be recalibrated.

Finally, we can compare values that enter market risk model. CNB's key interest rate in the first half of 2011 was 9%, in the second half of the year CNB lowered it to 7%. In our computation, we expected interest rate to be stable for whole 2011 under the baseline scenario or to rise to 11% under the adverse scenario. The decrease of key interest rate, which is assumed to be leading indicator for other interest rates, would positively affect available–for–sale securities in balance sheets which would increase banks' profit. The effect on interest income from maturity gap between interest sensitive assets and liabilities is uncertain. It was hardly possible to anticipate this change in interest rate, as CNB had announced no changes in its interest rate for the first half of 2011 when our survey was made. As the banks' financial report for 2011 are not available yet, we cannot compare the real effect of interest rate decrease. Regarding exchange rates, the difference between real and expected exchange rates is rather small.

Table 7.3: Revised variables for market risk in Croatia.

	Real value	Baseline	Adverse
i_cnb	7%	9%	11%
er_eur	7.49	7.01	7.29
er_usd	5.49	5.27	5.00

Source: Author's computations. Real values refers to Q3 2011 as Q4 2011 values were not available, baseline and adverse scenarios to Q4 2011. Variables *i_cnb*, *er_eur* and *er_usd* indicate CNB's key interest rate, HRK/EUR and HRK/USD exchange rates.

7.2 Data for Serbia

In Table 7.4 we show real values of macroeconomic variables used in credit risk models for Serbian corporate and household sectors. Growth rate of nominal interest rate and inflation used in credit models for baseline scenario were due to time lags the values observed in reality. As in case of Croatian GDP growth we overestimated the rate of its growth for Serbian economy. Although there was a positive growth at the end of 2010, growth rate of 1.52% is much lower than expected rate, which was 3.3%. On the other hand, the appreciation of Serbian dinar against euro was greater than expected and the change in unemployment rate shows different path than we assumed one year ago. We still do not have EU's GDP values for the last quarter of 2011, but the Q3 2011 value of GDP growth indicates that our estimation might not be much biased.

By putting obtained values of macro variables into the model expressed by Equation 5.4 for corporate sector and Equation 5.5 for household sector we can compare obtained probabilities of default with real, baseline and adverse values. Real probabilities of default in Q3 2011[3] are 20.45% and 7.65% for corporate sector and households, respectively. Estimated corporate probability of default in baseline scenario was almost equal to real value.

For households, probability of default turned to be higher than estimated values under both scenarios. However, models seem to be less biased than

[3] Q4 2011 values were not available, thus we used previous quarter as an approximation.

Table 7.4: Revised explanatory variables that enter credit risk models for Serbia.

Corporate sector	Time lag	Real value (%)	Baseline (%)	Adverse (%)
g_srb	-4	1.5	3.3	-4.3
g_eu	0	1.4	1.4	-0.9
er_eur	-1	-4.7	-1.0	- 6.0
Household sector	**Time lag**	**Real value (%)**	**Baseline (%)**	**Adverse (%)**
er_eur	0	-0.8	-0.4	-1.1
u	0	1.8	-4.3	4.5
i	-3	23.3	23.3	60.8
π	-4	16.2	16.2	16.2

Source: Author's computations. Real values refer to Q4 2011, baseline and adverse scenarios were computed in Chapter 5. Variables *g_srb*, *g_eu*, *er_eur*, u, i and π represent growth rates of Serbian and EU 15's GDPs, RSD/EUR exchange rate, unemployment rate, nominal interest rate, and inflation, respectively. Values are showed with respect to time lag in which they appear in the model (for example, Serbian GDP growth rate of 1.52% is the value of Q4 2010, which due to time lag appear in the model that estimates Q4 2011 situation).

in case of Croatia, surprisingly, regarding that we used longer time series for Croatian credit risk models and thus we expected these models to be more robust.

Table 7.5: Credit risk macro stress–testing results for real, revised, baseline and adverse scenarios in Serbia.

Value (%)	Real	Revised	Baseline	Adverse
Corporate default rate	20.45	21.31	20.22	25.21
Relative to actual scenario	–	+4	-1%	+23%
Household default rate	7.65	5.27	4.78	6.58
Relative to actual scenario	–	-31	-38%	-14%

Source: Author's computations. Real values refer to Q3 2011 and shows known values, baseline and adverse scenarios estimate Q4 2011 values.

As a next step, we put revised values of macro variables into credit risk models in order to check their appropriateness. Again, obtained probabilities of default do not fit real ones perfectly, which is evident since the models never explain reality in its whole complexity. Moreover, real values are from Q3 2011 and revised values estimate Q4 2011 situation. Nevertheless, the 31 % difference between estimated and real probabilities of default in case of corporates suggests that, in line with results of analysed Croatian credit risk models, the models for Serbia could be subjects to further exploration.

Table 7.6: Revised variables for market risk in Serbia.

	Real value	Baseline	Adverse
i_nbs	9.75%	12.5%	13.5%
er_eur	104.64	105.1	104.4
er_usd	80.87	82.4	85.5

Source: Author's computations.Real values refers to Q4 2011, baseline and adverse scenarios to estimated Q4 2011. Variables i_nbs, er_eur and er_usd indicate NBS's key interest rate, RSD/EUR and RSD/USD exchange rates.

Table 7.6 provides revised values of variables that enter market risk model. At the beginning of 2011 NBS had announced the increase of its key interest rate to 12.5% in response to accelerating inflation. Consequently, the inflation started to decrease during the second quarter of 2011 but the increase in leading interest rate caused the rise in banks' interest rates. Next, GDP's quarterly growth rates in 2011 were lower than in 2010. Presumably, the economic conditions led NBS to lower its interest rate for several times from the second half of 2011, resulting in the rate of 9.75% at the end of year. Comparing real and expected exchange rates we see that the difference is not significant. Regarding market risk variables we can see the similar situation as in case of Croatia with the same implications as were stated above.

Chapter 8

Conclusion

This thesis reviewed macro stress–testing methodology and applied it on real aggregate and individual bank's data in Croatia and Serbia. The aim of the study was to answer the questions whether we are able to build macro stress–testing framework using publicly available data for Croatia and Serbia and whether the stress tests can reveal possible risks to individual banks and threats to financial stability in these countries. The outcome of the study demonstrates that even with limited data the consistent stress tests can be developed under simplifying assumptions. In Chapter 6, we have shown that there are some banks that can have problems with fulfilling the regulatory minimum capital requirements both under the baseline and the adverse scenarios. Accordingly, the calculated capital injection that should prevent banks from possible failures reflects the potential fiscal costs to the government.

The baseline and the adverse scenarios were set to project macroeconomic variables for the end of 2011. The baseline scenario described the most likely future situation using various macroeconomic forecasts. The adverse scenario reflected the situation that occurred during the recent crisis, thus, data originated in 2008–2010. The macro stress tests were constructed in such a way that they captured the linkage between macroeconomic factors (GDP growth, inflation rate, interest rate etc.) and banks' balance–sheet items through the macro credit risk models, which were based on Wilson (1997a,b) approach. The models expressed dependent variable in the logistic form. For each country the models were developed for corporate and household sectors separately, reflecting sector's different sensitivities to macroeconomic movements. These satellite models estimated the sector–specific default rates (expressed in terms of non–performing loans to total loans) for the end of 2011 using the past data and the 2011 macro forecasts. The default rates were then used for the calculation of individual bank's losses that arose from credit risk exposures. For each bank we estimated also market risk losses. Due to time lag in publishing, banks' balance–sheet data were those of 2009. Both losses entered the computation of capital adequacy ratios (CAR) under the baseline and the adverse scenario at the end of 2011.

In case of Croatia, we considered nine largest banks that accounted for more than 90% of total banking sector assets in 2009. Under the baseline scenario we detected one foreign–owned large bank that had the CAR below the regulatory minimum level of 12%. Under the adverse scenario, there emerged two more banks with the CAR below the threshold, one of them was medium–sized state–owned bank and the second one was large foreign–owned bank. Under the adverse scenario, the estimated capital injection that would be needed to bring these banks to 12 % CAR threshold amounted for almost 0.27% of 2009 GDP in Croatia. In Serbia, we analysed ten major banks that accounted for 70% of banking sector assets in 2009. Similarly to situation in Croatia, there was one state–owned bank that did not fulfil the capital requirements under the baseline scenario and two banks (large state–owned and medium–sized foreign bank) with the same difficulties under the adverse scenario. In terms of the share of GDP the estimated capital injection was larger than in case of Croatia, accounting for 0.33% of Serbian GDP in 2009.

As an extension to Master Thesis this thesis provides the comparison between estimated macroeconomic variables including corporate and household probabilities of default under both scenarios with real end–2011 values of these variables. We have shown that estimated macroeconomic situations in the baseline scenarios, based on forecasts of leading international forecast organisations, were mostly only slightly different from reality. In order to check the appropriateness of credit risk models developed in Chapter 4, we used latest macro variables and ran these models again. Obtained probabilities of default were still different from real ones, partly due to the fact, that real PDs for Q4 2011 have not been available yet and we used Q2 – Q3 2011 values as approximations. Nevertheless, we believe that for the future research, it would be appropriate to revise models' coefficients and explanatory variables. Generally, time series used in stress tests are often rather short and macroeconomic situations unstable in time, thus the periodical reviews of stress–testing models are very useful.

The stress tests are effective tools for regulators and supervisors as they can reveal potential threats to financial stability. However, we should bear in mind that the results should be interpreted with caution as we faced data limitation and relatively short time series. On the other hand the models set in the thesis are intuitive and transparent and can be further developed when more data are available.

This work contributes to current stress testing literature by analysing the countries that have not been considered in detail in the stress tests and by covering periods prior to, during and after the recent financial crisis. As the large part of surveys conducted the stress tests before the crisis, recent data can show new and interesting results. Also, the framework provided in the study can be applied on other emerging markets that face similar data limitations.

Possible extensions for future research lie in broadening the range of risks that could be considered in the stress–testing framework, especially by adding liquidity tests and contagion analysis. Time horizon might be prolonged from one up to three years so that shocks can fully translate into deterioration of financial performance of banks and the whole system. In line with it, the attention should be paid to problems of endogeneity of risk and feedback effects. Next, it might be useful to revise theoretical models and variables if more data are available in order to check the models for parameters' instability and to increase their predictive power. Finally, in the future the stress–testing framework could be applied to more countries, especially to emerging markets, in which the stress–testing methods are still underdeveloped.

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Appendix A

Financial Soundness Indicators

Table A.1: Financial Soundness Indicators – Core set

Capital adequacy	Regulatory capital to risk–weighted assets Regulatory Tier 1 capital to risk–weighted assets Non–performing loans net of provisions to capital
Asset quality	Non–performing loans to total gross loans Sectoral distribution of loans to total loans
Earnings and profitability	Return on assets Return on equity Interest margin to gross income Non–interest expenses to gross income
Liquidity	Liquid assets to total assets (liquid asset ratio) Liquid assets to short–term liabilities
Sensitivity to market risk	Net open position in foreign exchange to capital

Source: IMF, http://www.imf.org/external/np/sta/fsi/eng/fsi.htm.

Table A.2: Financial Soundness Indicators – Encouraged set

Deposit–takers	Capital to assets Large exposures to capital Geographical distribution of loans to total loans Gross asset position in financial derivatives to capital Gross liability position in financial derivatives to capital Trading income to total income Personnel expenses to noninterest expenses Spread between reference lending and deposit rates Spread between highest and lowest interbank rate Customer deposits to total (non–interbank) loans Foreign–currency–denominated loans to total loans Foreign–currency–denominated liabilities to total liabilities Net open position in equities to capital
Other financial corporations	Assets to total financial system assets Assets to GDP
Non–financial corporations sector	Total debt to equity Return on equity Earnings to interest and principal expenses Net foreign exchange exposure to equity Number of applications for protection from creditors
Households	Household debt to GDP Household debt service and principal payments to income
Market liquidity	Average bid–ask spread in the securities market Average daily turnover ratio in the securities market
Real estate markets	Residential real estate prices Commercial real estate prices Residential real estate loans to total loans Commercial real estate loans to total loans

Source: IMF, http://www.imf.org/external/np/sta/fsi/eng/fsi.htm.

Appendix B

Additional Specifications to Credit Risk Models

Table B.1: Correlation coefficients for macroeconomic variables in Serbia.

5% critical value (two–tailed) = 0.3809 for n = 27
(using the observations Q1 2004–Q3 2010)

g_srb	*p*	*u*	*ind*	*er_n*	
1.0000	0.3541	−0.0389	0.7037	0.2859	*g_srb*
	1.0000	0.3675	0.2655	−0.1048	*p*
		1.0000	0.0226	0.1245	*u*
			1.0000	0.2996	*ind*
				1.0000	*er_n*

er_r	*er_usd*	*er_eur*	*i*	*r*	*g_eu*	
0.2568	−0.4979	−0.3662	0.1008	0.0486	0.5831	*g_srb*
0.1349	0.1384	0.0049	0.3020	0.1247	0.1811	*p*
0.3448	0.3981	0.0563	−0.1321	0.1635	0.3848	*u*
0.1987	−0.4922	−0.2267	−0.1068	0.0083	0.6705	*ind*
0.9233	−0.6679	−0.8554	−0.2975	0.2573	0.5761	*er_n*
1.0000	−0.5105	−0.8138	−0.2375	0.3191	0.5382	*er_r*
	1.0000	0.7822	−0.0333	−0.1737	−0.2931	*er_usd*
		1.0000	−0.0453	−0.2295	−0.3028	*er_eur*
			1.0000	0.2115	−0.3869	*i*
				1.0000	0.1768	*r*
					1.0000	*g_eu*

Source: Author's computations. Annotations: *g_srb* and *g_eu* are GDP growths in Serbia and the EU 15, *p* is inflation (PPI), *u* is unemployment rate growth, *ind* is industrial production growth, *i* and *r* are nominal and real interest rate growths, *er_n*, *er_r*, *er_usd* and *er_eur* are growths in nominal and real effective exchange rates and in RSD/USD and RSD/EUR exchange rates. All variables are expressed in terms of the growth rates. The higher the correlation coefficient for the two variables in absolute value, the greater the correlation among these variables.

Table B.2: Correlation coefficients for macroeconomic variables in Croatia–Part 1.

5% critical value (two–tailed) = 0.2973 for n = 44
(using the observations Q1 2000–Q4 2010)

g_hr	g_eu	p	u	er_n	er_r	er_eur	
1.000	0.593	0.133	−0.531	−0.402	0.259	−0.163	g_hr
	1.000	−0.115	0.048	−0.019	0.230	−0.304	g_eu
		1.000	−0.199	−0.103	−0.250	−0.203	p
			1.000	0.616	−0.113	0.109	u
				1.000	0.318	0.578	er_n
					1.000	0.161	er_r
						1.000	er_eur

er_usd	i	i_st_cp	i_st_hh	i_lt_cp	i_lt_hh	r	
−0.473	−0.281	−0.245	−0.500	−0.220	−0.523	−0.582	g_hr
−0.008	−0.298	−0.371	−0.265	−0.510	−0.569	−0.377	g_eu
0.126	−0.226	−0.178	0.140	0.328	0.023	−0.431	p
0.606	−0.231	−0.347	0.251	−0.239	0.214	0.164	u
0.582	−0.208	−0.202	0.271	0.177	0.137	0.108	er_n
0.073	−0.153	−0.103	−0.308	−0.020	−0.135	−0.205	er_r
−0.071	0.039	0.157	0.221	0.315	0.068	0.156	er_eur
1.000	−0.256	−0.283	0.105	0.051	0.261	0.195	er_usd
	1.000	0.940	−0.075	0.178	0.311	0.621	i
		1.000	−0.110	0.284	0.282	0.615	i_st_cp
			1.000	0.391	0.317	0.133	i_st_hh
				1.000	0.485	0.160	i_lt_cp
					1.000	0.385	i_lt_hh
						1.000	r

Source: Author's computations. Annotations: g_hr and g_eu are GDP growths in Croatia and the EU 15, p is inflation (CPI), u is unemployment rate growth, er_n, er_r, er_usd and er_eur are growths in nominal and real effective exchange rates and in RSD/USD and RSD/EUR exchange rates, i_st_cp, i_st_hh, i_lt_cp and i_lt_hh are nominal lending interest rates on short term and long term credits for corporates and households, and i and r are nominal and real interest rates. All variables are expressed in terms of the growth rates. The higher the correlation coefficient for two variables in absolute value, the greater the correlation among these variables.

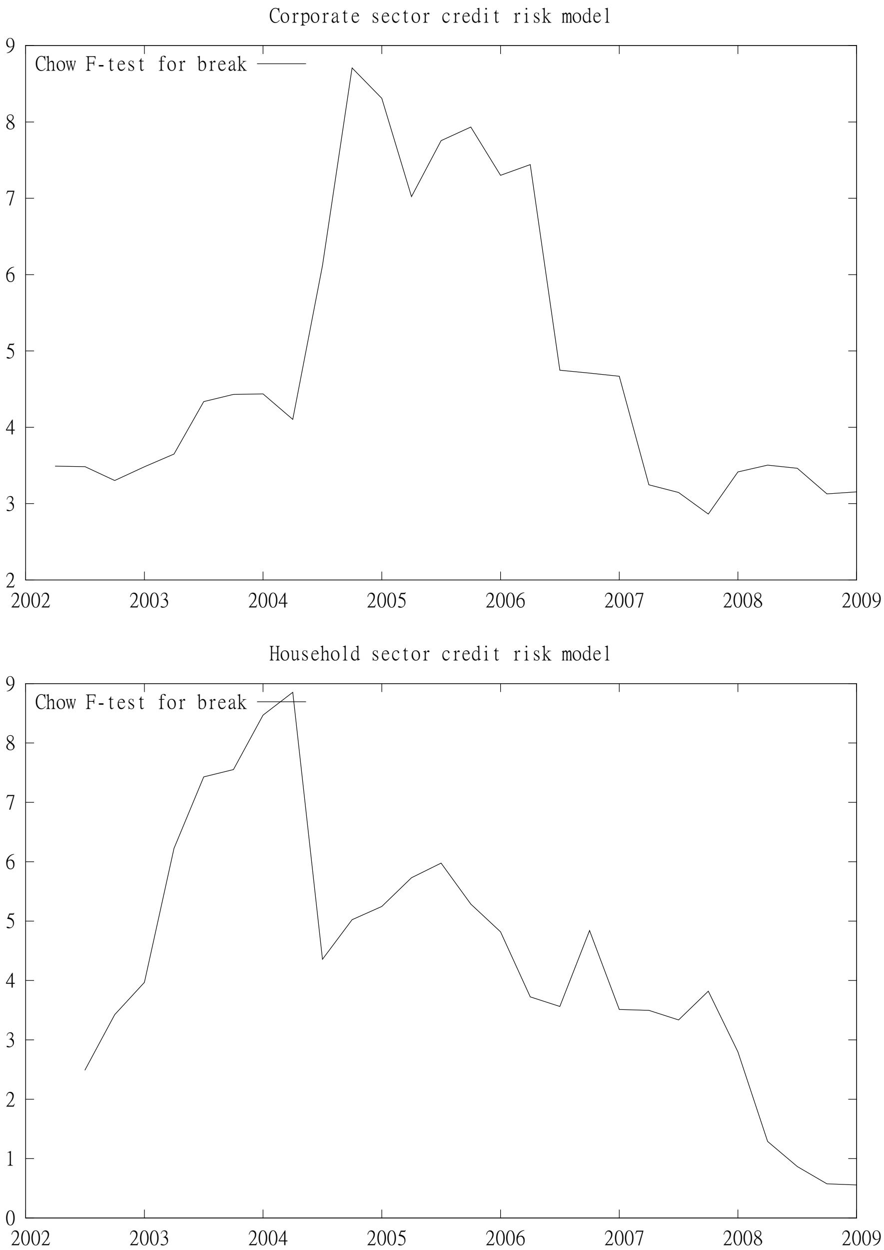
Table B.3: Correlation coefficients for macroeconomic variables in Croatia–Part 2.

5% critical value (two–tailed) = 0.2973 for n = 44
(using the observations Q1 2000–Q4 2010)

r_st_cp	*r_st_hh*	*r_lt_cp*	*r_lt_hh*	*ir_spread*	*y_disp*	*w_real*	
0.340	−0.665	0.274	−0.664	−0.280	0.672	0.071	*g_hr*
0.245	−0.338	0.166	−0.497	−0.331	0.619	−0.044	*g_eu*
−0.008	−0.488	−0.006	−0.335	−0.352	0.352	−0.191	*p*
−0.099	0.350	−0.124	0.271	−0.115	−0.029	−0.010	*u*
−0.099	0.285	−0.033	0.214	−0.146	0.089	−0.017	*er_n*
0.214	−0.215	0.195	−0.234	0.000	0.018	−0.209	*er_r*
−0.043	0.245	0.008	0.193	−0.016	−0.058	0.170	*er_eur*
−0.221	0.306	−0.155	0.350	−0.145	0.035	0.113	*er_usd*
−0.097	0.278	−0.142	0.401	0.637	−0.409	0.189	*i*
−0.139	0.284	−0.173	0.422	0.494	−0.444	0.218	*i_st_cp*
−0.221	0.428	−0.135	0.281	−0.037	−0.225	−0.092	*i_st_hh*
−0.185	0.158	−0.083	0.291	0.244	−0.138	0.031	*i_lt_cp*
−0.181	0.373	−0.102	0.573	0.384	−0.351	0.141	*i_lt_hh*
−0.602	0.874	−0.567	0.925	0.510	−0.496	0.436	*r*
1.000	−0.517	0.981	−0.612	−0.067	0.206	−0.139	*r_st_cp*
	1.000	−0.431	0.914	0.308	−0.472	0.406	*r_st_hh*
		1.000	−0.519	−0.075	0.180	−0.087	*r_lt_cp*
			1.000	0.392	−0.489	0.448	*r_lt_hh*
				1.000	−0.407	0.053	*ir_spread*
					1.000	0.228	*y_disp*
						1.000	*w_real*

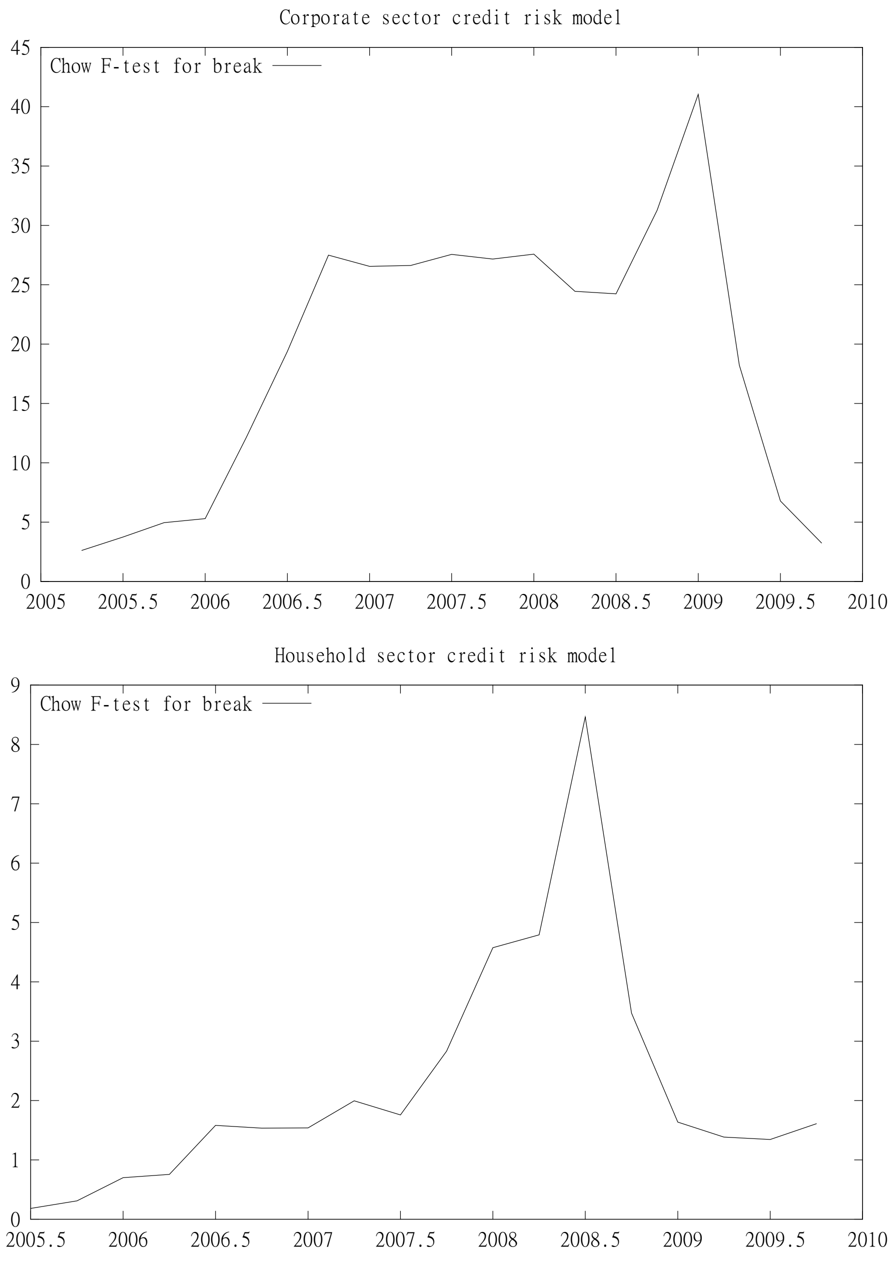
Source: Author's computations. Annotations: *r_st_cp*, *r_st_hh*, *r_lt_cp* and *r_lt_hh* are real lending interest rates on short term and long term credits for corporates and households, *ir_spread* is spread between interest rates on credits and deposits, *y_disp* is disposable income, and *w_real* is real wage. All variables are expressed in terms of the growth rates. The higher the correlation coefficient for two variables in absolute value, the greater the correlation among these variables.

Figure B.1: Chow's F–test for structural break at an unknown point for Croatia.



Source: Author's computations. Quandt likelihood ratio test for structural break at an unknown point, with 15 percent trimming: structural break found at observation Q4 2004 and Q3 2005 for corporate's model and at Q3 2004 and Q4 2006 for household's model, both significant at the 1% level.

Figure B.2: Chow's F–test for structural break at an unknown point for Serbia.



Source: Author's computations. Quandt likelihood ratio test for structural break at an unknown point, with 15 percent trimming: structural break found at observation Q1 2009 for corporate's model and at Q3 2008 for household's model, both significant at the 1% level.

Table B.4: Tests for assumptions of OLS model–results for corporate sector credit risk model in Croatia and Serbia.

Model for Croatia	Test	Null hypothesis	P–value
Normality of residuals	Shapiro–Wilk	Normally distributed error	0.9725
Homoscedasticity	White's	No heteroscedasticity	0.6986
Autocorrelation	LMF	No autocorrelation	0.2621
Model for Serbia	Test	Null hypothesis	P–value
Normality of residuals	Shapiro–Wilk	Normally distributed error	0.5525
Homoscedasticity	White's	No heteroscedasticity	0.2366
Autocorrelation	LMF	No autocorrelation	0.3529

Source: Author's computations.

Table B.5: Tests for assumptions of OLS model–results for household sector credit risk model in Croatia and Serbia.

Model for Croatia	Test	Null hypothesis	P–value
Normality of residuals	Shapiro–Wilk	Normally distributed error	0.0397
Homoscedasticity	White's	No heteroscedasticity	0.7143
Autocorrelation	LMF	No autocorrelation	0.9013
Model for Serbia	Test	Null hypothesis	P–value
Normality of residuals	Shapiro–Wilk	Normally distributed error	0.2150
Homoscedasticity	White's	No heteroscedasticity	0.2560
Autocorrelation	LMF	No autocorrelation	0.2790

Source: Author's computations.

Appendix C

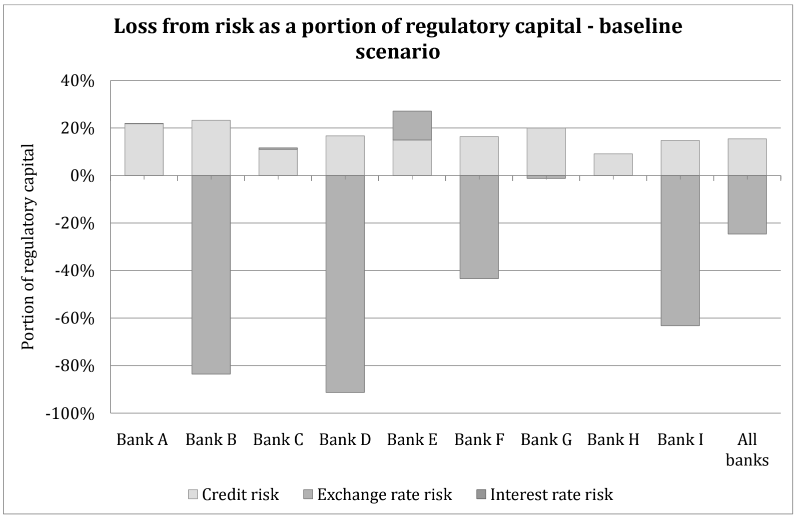
Specification of Stress–Testing Results

Table C.1: Write–off rates in Croatian and Serbian banks.

	Croatia (in %)	Serbia (in %)
Bank A	19.59	12.69
Bank B	34.52	7.20
Bank C	2.43	9.80
Bank D	13.50	28.00
Bank E	0.78	N/A
Bank F	33.91	17.18
Bank G	21.91	44.84
Bank H	27.71	19.31
Bank I	15.45	2.57
Bank J	–	10.64
Average	23.80	18.71

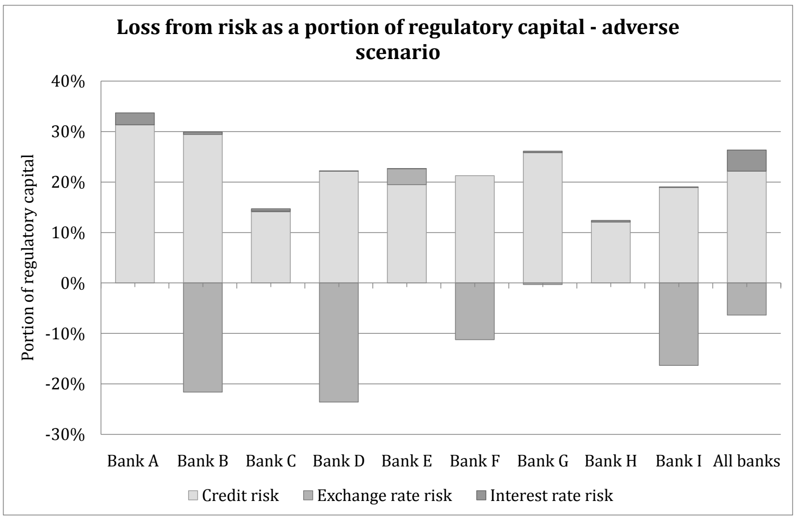
Source: Author's computations. Data are from individual bank's 2009 financial reports. In case of Croatia, the write–off rates of Bank C and E were not counted for the average rate due to their relatively low value. Similarly, Bank I was not considered in Serbian banks' average write–off rate.

Figure C.1: Portion of risks relative to capital in baseline scenario for Croatian banks.



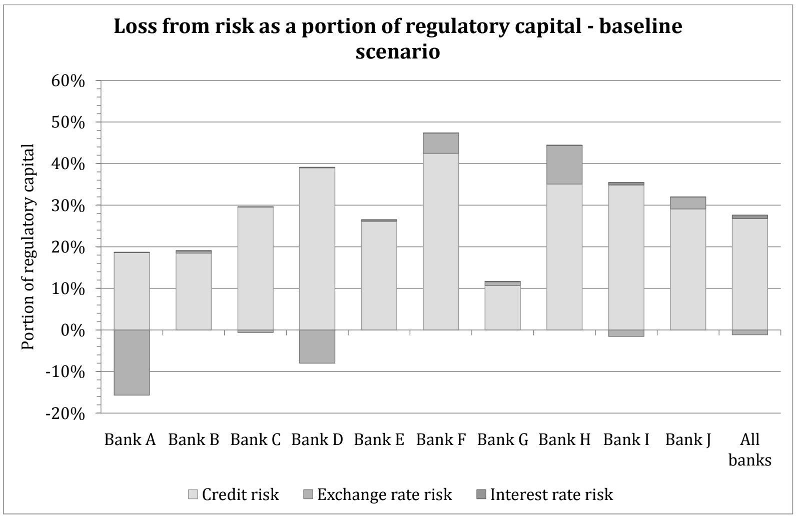
Source: Author's computations.

Figure C.2: Portion of risks relative to capital in adverse scenario for Croatian banks.



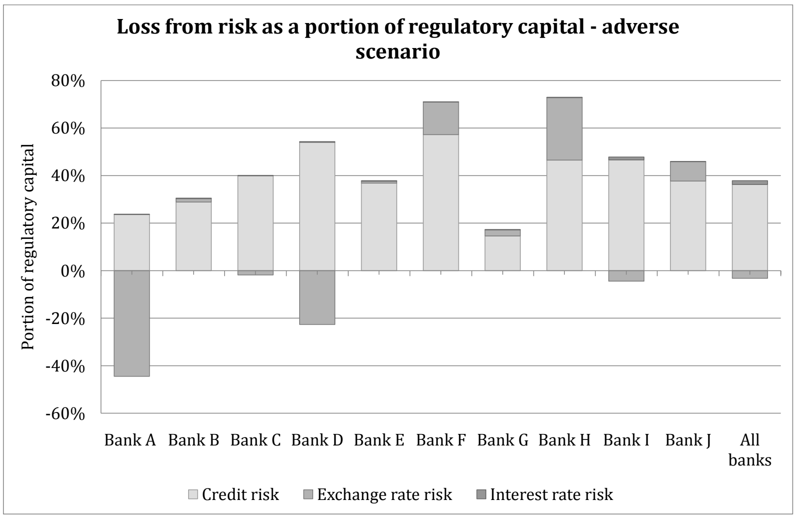
Source: Author's computations.

Figure C.3: Portion of risks relative to capital in baseline scenario for Serbian banks.



Source: Author's computations.

Figure C.4: Portion of risks relative to capital in adverse scenario for Serbian banks.



Source: Author's computations.