JEL Classification: E44, E47, G21
Keywords: banking sector, credit risk, stress tests

Dynamic Stress Testing: The Framework for Assessing the Resilience of the Banking Sector Used by the Czech National Bank*

Adam GERŠL—Joint Vienna Institute, Czech National Bank (on leave) and Faculty of Social Sciences, Charles University, Prague (adam.gersl@gmail.com)

Petr JAKUBÍK—European Insurance and Occupational Pensions Authority (EIOPA), Czech National Bank (on leave) and Faculty of Social Sciences, Charles University, Prague (petr.jakubik@eiopa.europa.eu)

Tomáš KONEČNÝ—Czech National Bank (tomas.konecny@cnb.cz)

Jakub SEIDLER—Czech National Bank and Faculty of Social Sciences, Charles University, Prague (jakub.seidler@cnb.cz), *corresponding author*

Abstract

This paper describes the current stress-testing framework used at the Czech National Bank (CNB) to test the resilience of the banking sector. Macroeconomic scenarios and satellite models linking macroeconomic developments with key risk parameters and assumptions for generating dynamic stock-flow consistent behavior of individual bank balance-sheet items are discussed. Examples from past CNB Financial Stability Reports are given and emphasis is put on conservative calibration of the stress-testing framework so as to ensure that the impact of adverse scenarios on the banking sector is not under-estimated.

1. Introduction

The aim of this paper is to describe the methodology of the current macro stress-testing framework used by the Czech National Bank to assess the resilience of the Czech banking sector. We focus primarily on solvency stress tests, i.e., on stress tests that capture the risk of a large part of the banking sector becoming insolvent due to a shortage of regulatory capital.[1] This type of "macro" stress tests of banks has become a standard tool among central banks and regulatory authorities for assessing the vulnerabilities of the banking sector as a whole (see, for example, Foglia, 2009, or Drehmann, 2009, and references therein).

The paper discusses the gradual development of the CNB's stress-testing methodology over the last ten years to illustrate the main challenges in stress-testing modeling and how these challenges have been tackled by the CNB. We also describe the development of so-called satellite models, which serve as a link between the tra-

* The authors would like to thank Attila Csajbók, Jan Frait, Michal Hlaváček, Pavol Jurča, Claus Puhr, Christian Schmieder and the journal referees for helpful comments and useful recommendations. However, all errors and omissions are those of the authors. The findings, interpretations and conclusions expressed in this paper are entirely those of the authors and do not represent the views of any of the above-mentioned institutions. The authors acknowledge the support of the Czech National Bank (CNB Research Project No. C1/10) and GAČR 403/10/1235.

[1] Liquidity stress testing is conducted in a separate framework (see the methodology described in detail in Geršl et al., 2011). Nevertheless, there is a link between these two frameworks, as some of the liquidity shocks for individual banks are dependent on the trajectories of the risks and returns of these banks in the solvency stress tests.

jectories of the main macroeconomic variables provided by the CNB's official prediction model and the trajectories of key variables of financial sector risks. We illustrate both the historical specification of these models and the re-estimated versions that are currently used for estimating aggregated credit risk for the corporate, consumer and household sectors, and also models for estimating the credit dynamics of these portfolios. Attention is further devoted to the model of property prices and profits of the banking sector and other relevant assumptions regarding banking sector behavior that are necessary for building a reliable and robust stress-testing framework. This paper provides an update and a much more detailed description of the CNB's stress-testing methodology in comparison to Geršl and Seidler (2010), which provided only a short overview of the CNB's recent stress-testing framework.

As the risk jeopardizing the banking sector might be rapidly evolving, we also debate the possibility of testing different ad-hoc shocks, including concentration risk in portfolios, the risk of excessive dividend payouts, default of cross-border interbank exposures and sovereign risk in banks' balance sheets. The methodology is illustrated empirically on the stress-test results from Financial Stability Report 2011/2012 published in June 2012 with a stress scenario entitled Europe in Depression capturing the relevant risks for the Czech economy as assessed in mid-2012. Finally, the paper argues that the stress-testing methodology should be set in a conservative manner and should slightly overstate the risks, since the estimated elasticities in mostly linear (but also non-linear) models may change significantly for the worse when risks materialize. Conservative calibration of stress tests ensures that the impact of shocks on the banking sector will not be underestimated in the event of adverse developments.

The paper is structured as follows: Section 2 reviews the relevant literature on stress testing, while Section 3 describes the history and gradual development of the CNB's stress tests. Section 4 explains in detail the individual building blocks of the CNB stress-testing framework and illustrates the methodology using a stress scenario from the CNB's Financial Stability Report 2011/2012. Section 5 focuses on the arguments for conservative calibration of the parameters used in stress testing. Finally, Section 6 concludes the paper by identifying challenges for the future development of stress tests in general.

2. Review of the Literature on Stress Testing of the Banking Sector

The earliest banking sector stress-testing models, which were initially based on simple historical scenarios linking macroeconomic developments with financial sector variables (e.g., Blaschke et al., 2001), have been developed into more sophisticated models integrating market, credit and interest rate risk and capturing inter-institution contagion and some feedback effects between the financial sector and the real economy. These relatively complex models have become regular tools for analyzing the resilience of the financial sector—see, for example, Danmarks Nationalbank (2010, p. 45), Oesterreichische Nationalbank (2010, p. 51), Norges Bank (2010, p. 49), the RAMSI (Risk Assessment Model for Systemic Institutions) of the Bank of England (Aikman et al., 2009), and the European Banking Authority (2011).

Nevertheless, the global financial crisis uncovered deficiencies in the stress-testing methodologies used in many countries. Before the crisis, many tests had been wrongly indicating that the sector would remain stable even in the event of sizeable shocks (Haldane, 2009; Borio et al., 2012). These deficiencies were related not only to the configuration of the adverse scenarios used, which had initially seemed implausibly strong but were often exceeded in reality, but also to the shock combination assumed, which had not been adequately anticipated in the scenarios (Ong and Čihák, 2010; Breuer et al., 2009). A role was also played by deficiencies in model calibration and in the assumed behavior of banks and markets, and by the absence of testing of liquidity risk alongside traditional financial risks (in particular credit risk and interest rate risk), since the distress after the Lehman failure confirmed the importance of the spiral between market and funding liquidity and its fragile link to the solvency of institutions (Gorton, 2009; Brunnermeier et al., 2009). This problem in stress-testing frameworks is also demonstrated by Ong and Čihák (2010) using the example of Iceland, where the banking sector collapsed in the fall of 2008 even though stress tests conducted in mid-2008 had indicated it was stable and resilient to various shocks.

Consequently, the assumptions and parameters used in stress tests are gradually being re-examined so that the tests can better capture the impact of strong shocks on the financial system. Stress tests are also becoming a standard tool in the new macroprudential framework (FSB, 2011; BCBS, 2012), though there are some doubts about their ability to serve as an early warning device (Borio et al., 2012). Still, despite a clear consensus on the importance of stress testing, there are many drawbacks related to the methodological approaches to stress tests and the construction of valid and severe scenarios (see, for example, Jakubík and Sutton, 2012). This holds especially for Central and Eastern European countries, such as the Czech Republic, which have relatively short time series and possible structural breaks. Some of the difficulties can be partially resolved. For example, Buncic and Melecky (2013) give some practical suggestions on some of these difficulties (such as how to construct stress scenarios if there are no stress periods in the estimation sample) and provide an empirical application of the proposed methodology to an Eastern European country's banking sector. In defense of stress testing, this is a relatively new tool[2] and hence could have been expected to undergo methodological development and refinement.[3] The recent financial turbulence has suggested some possible ways in which this methodological development should be directed. A recent report by the Basel Committee on Banking Supervision (BCBS, 2012) on best practices in macroprudential analyses emphasized the need to overcome the potential downward bias of risk prediction when using models estimated on calm-period data. This is in line with the conservative calibration approach applied at the CNB (see Section 5). The BCBS also proposed using a longer time horizon for stress tests, such as three to five years. This is in line with the CNB's stress-testing framework, which has recently extended its horizon from two to three years. Other good practices discussed in the report include more extensive use of granular data (such as on large exposures

[2] Tools based on various types of financial soundness indicators have traditionally been used to assess the resilience of financial institutions (Geršl and Heřmánek, 2008).

[3] The formal obligation of commercial banks to conduct stress tests on their own portfolios was only introduced by Basel II (for banks using advanced methods for calculating capital requirements), which was implemented in the EU in 2006–2007. However, there is now a set of CEBS/EBA guidelines related to stress testing in commercial banks (see Committee of European Banking Supervisors—CEBS, 2009).

and interbank exposures), higher integration of solvency and liquidity tests, and much more conservative estimation of bank pre-provision profits for stress periods than suggested by models—all of which are important components of the CNB's current stress-testing framework, as described in the following sections.

3. How the CNB's Stress-Testing Methodology Evolved

The CNB started stress testing in 2003. The original banking sector stress-testing methodology applied at the CNB was based on the IMF methodology used for FSAP missions (e.g., Blaschke et al., 2001; Čihák, 2005; Čihák and Heřmánek, 2005).[4] It was further elaborated in line with the IMF static stress-testing framework developed by Čihák (2007). Details of the initial stress-testing framework used at the CNB are provided by Čihák at al. (2007).

The CNB switched in 2006 from testing historical ad-hoc scenarios defined by a combination of shocks (e.g., a 20% rise in non-performing loans, a 15% exchange rate depreciation and an increase in interest rates) to using consistent macroeconomic scenarios generated by the CNB's prediction model.[5] The framework also included a contagion module within which a failure of a bank could cause a domino effect and impact the whole network of interconnected banks. In parallel, credit risk and credit growth satellite models were estimated to link macroeconomic developments with non-performing loans (NPLs) and credit growth (Jakubík and Heřmánek, 2008). This framework was used for the Financial Stability Reports published between 2007 and 2009. At this stage, the stress test combined static and dynamic features, as the projections for macro variables, credit risk (NPLs) and credit growth were at quarterly frequency for a horizon of one to two years (dynamic), while the stress-testing framework was still static in terms of allowing only one-off shocks and the "what-if" type of analysis with a one-year horizon (no quarterly modeling).

Such a mixed framework created an inconsistency regarding the different time horizons for different risks—market risk has a very short-term impact (measured in terms of days or, in the macro-framework, one quarter), while credit risk accumulates more slowly. Full propagation of a macroeconomic shock to new NPLs may take between three and eight quarters depending on the type of loan. However, the static framework allowed only a one-off shock with a one-year horizon, which often meant underestimation of credit risk (which would continue increasing the following year) and possible incorrect capture of market risk (for example, the price of bonds might have increased and decreased back within a year, so that on average the framework would show no impact).[6] These deficiencies finally led to the adoption of the "dynamic" stress-testing framework in late 2009 and early 2010, which is described later in this paper.

The satellite models mentioned above were developed to underpin the stress-testing exercise applied. First, the aggregate credit risk model was estimated to obtain the default rates of banks' loan portfolios. A detailed description of the model is

[4] The stress-testing methodology used by IMF FSAP missions has also developed considerably. The current stress-testing framework is described in Schmieder et al. (2011).

[5] The new Keynesian QPM model up to 2008, and the DSGE g3 model since 2009.

[6] In reality, this would be incorrect, as a weak bank could become insolvent within a year and the subsequent recovery of bond prices would not help it much. In the mixed framework, this was taken into account by taking the most severe value (of the four quarterly forecasted values for the next year).

provided in Jakubík (2007). Second, this model was later replaced by two models allowing breakdown into corporate and household loans (Jakubík and Schmieder, 2008). In all cases, a one-factor model that is one of the variants of the latent factor model, which belongs to the class of Merton structural models, was employed (e.g., Hamerle et al., 2004). This non-linear model enables some more extreme scenarios to be captured. Together with the two credit risk models, a credit growth model of a co-integrated VAR type was also included in the framework to better capture the credit growth in the Czech economy with its effect on the volume of risk-weighted assets. However, due to insufficient time series for household credit, only the aggregate credit growth model was estimated (for details see Jakubík and Heřmánek, 2008).

In mid-2009, the CNB significantly updated its banking sector stress-testing methodology in three respects. First, the tests were "dynamized" in the sense of switching to quarterly modeling of shocks and their impacts on banks' portfolios. This change was described in a box in the CNB's Financial Stability Report 2008/ /2009 (CNB, 2009, pp. 63–64) and in Geršl and Seidler (2010). Second, in the credit risk area, there was a changeover to "Basel II terminology" . While in the static and mixed framework new NPLs were projected and the related loan losses (provisions) were calculated as the amount of new NPLs times the NPL coverage ratio (loan loss provisions divided by loans calculated for individual banks), in the dynamic framework the credit risk involved several separate portfolios and used the standard parameters PD, LGD and EAD and related risk-weighted assets (based on these parameters using the IRB formula procedures specified in the Basel II approach to calculating capital requirements).[7] Another major innovation was the extension of the shock impact horizon from one to two years (or eight subsequent quarters) and later, in 2011, to three years. Finally, given the possibility of modeling the banking sector at quarterly frequency in the new updated stress-testing framework, stress tests could be run at higher frequency in a more convenient manner (quarterly rather than only annually or semi-annually).

Following the changes in the framework, all satellite models were further updated in early 2010. Together with the re-estimation of the two credit risk models, two credit growth models (one for households and one for corporations) replacing the aggregate credit growth model were estimated (see *Appendix 1*). Longer historical time series were used to improve the quality of all predictions. As the Basel II terminology requires not only PD (the default rate), but also LGD (one minus the recovery rate), three simple one-factor models were used to generate LGD for corporate, consumer and mortgage loans. However, given that the LGD on mortgages is clearly dependent on house prices (while the other two LGDs are dependent on macro variables such as GDP and unemployment), a model for Czech house prices estimated in Hlavacek et al. (2009) was used. Moreover, a simplified pre-provisions profit model was estimated on Czech data to forecast banks' profitability (before provisioning and accounting for market losses).[8]

This new framework was also subject to a vast verification (validation) exercise in late 2009, which—using the available satellite models—tested the predictive

[7] PD—probability of default; LGD—loss given default; EAD—exposure at default; IRB—internal ratings based.

[8] See Box 7 in FSR 2009/2010 (CNB 2010).

accuracy of the framework and compared the baseline prediction of the framework (for the one-year horizon) with the subsequent real turnout of selected variables such as default rates, NPLs and capital adequacy (for details see Geršl and Seidler, 2010, 2012). The final message of the exercise was that the framework is relatively robust and, if there are forecasting errors, it errs on the conservative side. From a prudential perspective, a conservative approach that slightly overestimates risks and underestimates buffers (such as capital or profitability) is appropriate (see Section 5).

The new dynamic framework with new satellite models was used for the first time in Financial Stability Report 2009/2010 (CNB, 2010) and with only slight adjustments in FSR 2010/2011 (CNB, 2011). Moreover, since early 2010 the stress tests have been conducted at quarterly frequency and published on the CNB website.

While the framework remains the main building block of the stress-testing exercises, over time new elements have been added and satellite models updated in order to reflect new data over the period of the global financial crisis. The current stress-testing framework described below was used for FSR 2011/2012 published in June 2012.

4. Current Stress Testing Framework of the CNB

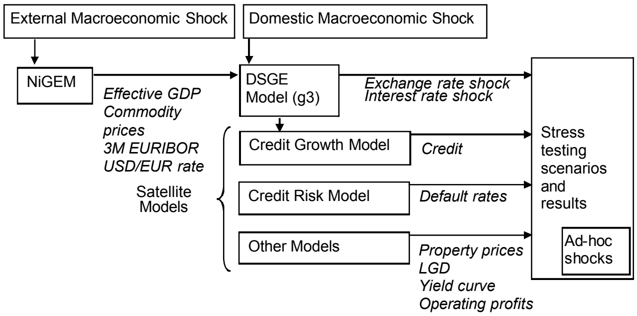
The stress-testing framework is dynamic in the sense that the predictions for macroeconomic and financial variables for individual quarters are reflected directly in the predictions for the main balance-sheet and flow indicators of banks. For each item of assets, liabilities, income and expenditures there is an initial (the last actually known) stock/flow, to which the impact of the shock in one quarter is added/ /deducted, and this final stock/flow/accumulated flow is then used as the initial value for the following quarter. This logic is repeated in all quarters for which the prediction is being prepared. Consistency between stocks and flows is ensured by linking the flows and stocks (so that any changes in profit, for example, are directly reflected in both liabilities and assets).

4.1 Alternative Macroeconomic Scenarios

Alternative macroeconomic scenarios serve as the starting point for stress testing in the current methodological framework. Stress (or adverse) scenarios are constructed based on the identification of risks to the Czech economy in the near future as seen by the CNB Financial Stability Department. To compare the stress outcome with the most probable outcome, a baseline scenario, i.e., the current official macroeconomic prediction of the CNB, is also used.

All the scenarios are designed using the CNB's official g3 prediction model, which is a DSGE (dynamic stochastic general equilibrium) model (Andrle et al., 2009). As this model is calibrated and not estimated, confidence intervals are not available and the scenarios thus represent central forecasts given the shocks assumed for selected variables in the model. The model focuses on the domestic economy, and thus the foreign variables relevant to the evolution of the small, open Czech economy are imposed exogenously in the model. Most of the baseline predictions for foreign variables (such as effective euro-area GDP growth, and inflation) are taken from the Consensus Forecasts publication, but for some (such as the 3M and 1Y Euribor and oil prices), market-based predictions are used. For the alternative scenarios, there

Scheme 1 Architecture of Stress Tests



is large discretion as to how the foreign trajectories will evolve. However, in order to ensure some macroeconomic consistency between the foreign macro variables, a NiGEM model for the global economy is used to generate the trajectories of foreign variables, which serve as inputs into the g3 model.[9] The external economic assumptions consist of the 3M Euribor, effective euro-area GDP and PPI, the USD/EUR exchange rate and selected commodity prices (Brent oil prices, gasoline prices and natural gas prices). They enter the g3 model, which then provides quarterly trajectories for the main domestic macro variables, such as real GDP and its components, inflation, wages and short-term interest rates (the 3M Pribor).

The g3 model does not include all the macro variables that are used for stress testing. Among the most important ones, it lacks the unemployment rate and more thorough yield curve modeling. Thus, the g3 predictions are supplemented with an estimate of the evolution of unemployment using Okun's law estimated for the Czech economy. In case of yield curves, the g3 model includes only the 3M Euribor (exogenous) and 3M Pribor (endogenous). Additional maturities—1Y domestic and foreign (euro-area) interbank rates and 5Y Czech and German government bond yields—are estimated using the current level of short-term rates, a prediction of future shorter rates and an expertly defined risk premium (which is rather small for 1Y rates, but can become quite large for 5Y maturities). Given the large uncertainty for 5Y bond yields in particular, stability of 5Y bond yields is often assumed for the baseline scenario. For the stress scenario, the expertly-defined risk premium is shocked based on expert judgment, various historical events or the past volatility of bond yields.

Scheme 1 describes the whole above-mentioned architecture of the stress-testing framework.

In practice, the stress scenarios are generated by assuming certain shocks to key macroeconomic variables, which then endogenously feed through the g3 model to generate the trajectories for all relevant macro variables. A typical shock would be, for example, a drop in (effective) euro-area GDP growth (which serves as a proxy for the demand for Czech exports), which feeds through the g3 model, causing a drop in domestic GDP growth (mainly due to lower net exports) and potentially lower

[9] The NiGEM model of the National Institute of Economic and Social Research is an estimated model which uses a "New-Keynesian" framework—agents are presumed to be forward-looking but nominal rigidities make the process of adjustment to external events slower.

inflation, lower domestic interest rates and some depreciation of the domestic currency, which could partly counterbalance the deflationary pressures. In practice, a set of shocks to both foreign variables (euro-area GDP growth, foreign interest rates and inflation, oil prices) and domestic variables (risk premia in money markets or in the exchange rate equation) is assumed, creating a consistent and severe but plausible macroeconomic scenario.

As to the size of the macroeconomic shocks, a combination of expert judgment and statistical analysis (based on historical data) is used. Moreover, the CNB Monetary and Statistics Department, which runs the g3 forecasting model, is consulted on the proposed sizes of the shocks, whether for GDP or for other variables (such as the exchange rate and interest rates). This approach prevents the shock sizes from being either too small (for example, if they were only based on a statistical distribution over a too-benign period) or too large (the interdepartmental discussion serves as a cross-check of the plausibility of the scenarios). On average, the size of shocks in the CNB's stress tests is regarded as relatively large both internationally (IMF, 2012) and within the Czech banking sector.[10] Nevertheless, as discussed further in the paper, we generally opt for a conservative calibration and prefer to err on the pessimistic side as to the size of the shocks.[11]

We can illustrate the way of calibrating the shocks on the main macroeconomic shock that forms part of virtually all the stress scenarios—namely, a decline in domestic GDP, which in almost all the scenarios is caused by a drop in external demand (effective euro-area GDP) due to the high degree of openness of the Czech economy. While different shock sizes to euro-area GDP growth are used in different stress scenarios, the most severe scenario is usually designed backwards by asking, for example, "What decline in euro-area GDP would cause domestic GDP to decline similarly as in 2009?" (or, alternatively, the largest drop in GDP seen over the past 15 years, both of which are expert-judgment-based shock sizes) or "What decline in euro-area GDP would cause a decline in domestic GDP equal to two to three standard deviations of the domestic GDP growth distribution over the past 15 years?" (a statistically supported shock size). For example, the stress tests prepared as part of the 2011 IMF FSAP mission (IMF, 2012) used a scenario defined statistically as a drop in domestic GDP equal to 2.5 standard deviations.

We illustrate the construction of the stress scenarios using the scenarios described in the CNB's Financial Stability Report 2011/2012 published in June 2012. Here, two scenarios were used—one baseline scenario and one adverse scenario called "Europe in Depression", which captured the most important risks to the Czech economy as assessed in mid-2012.

[10] Only anecdotal evidence is available on comparison of the sizes of the shocks with the stress scenarios applied by banks themselves in their own risk management practice. When the CNB started a project of joint bottom-up stress tests with selected banks (CNB, 2009), the participating banks were quite surprised by the level of stress imposed by the suggested scenarios. The CNB's scenarios started to serve as "worst-case" scenario benchmarks in many of the participating banks, but generally the banks' risk management teams welcomed this conservative approach, which was warranted by the general uncertainty about the economic outlook both in Europe and in the Czech Republic during the global financial crisis of 2008–2010.

[11] Franta et al. (2011), using Bayesian VAR fan charts, provide some evidence on the probability of the CNB's stress scenarios. They show that their probability is indeed very low (in terms of GDP shocks, for example, below 2%) and can thus be labeled as sufficiently adverse.

Figure 1 Alternative Scenarios: Real GDP Growth (%)

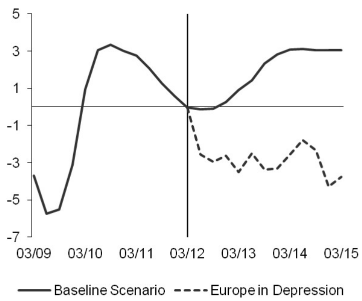


Figure 2 Alternative Scenarios: Exchange Rate (CZK/EUR)

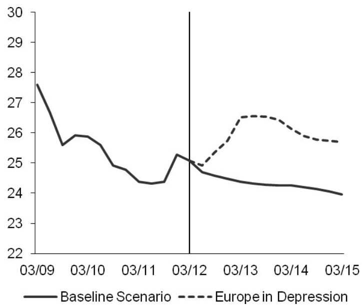


Figure 3 Alternative Scenarios: 3M PRIBOR (%)

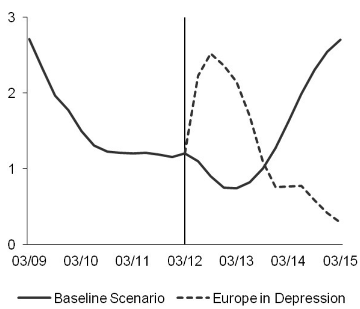
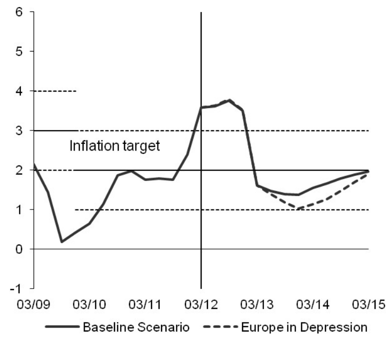


Figure 4 Alternative Scenarios: Inflation (%)



Note: The path for the baseline scenario in the first two years is based on the CNB's official prediction; beyond this horizon it is extended toward the expected long-term equilibrium values.

Sources: CNB, CNB calculation

Figures 1–4 show the trajectories for the main macro variables for both the baseline and adverse scenarios. While the baseline scenario is based on the official May 2012 macroeconomic forecast published in Inflation Report II/2012 and predicts that the Czech economy will switch to stagnation this year and will recover in 2013, the adverse Europe in Depression scenario assumes a long-lasting adverse trend in economic activity in Europe. This could come as a result of persistent uncertainty regarding a credible resolution of the debt crisis in the euro area, intensive deleveraging and new regulations curbing the credit supply of the banking sector. The environment of high uncertainty is exacerbated by a surge in oil and energy commodity prices and an increase in consumer prices as a result of escalating geopolitical uncertainty and continuing growth in demand from Asian economies.

The combination of these factors, which were imposed as changes in the exogenous variables in the g3 model (lower-than-expected euro area GDP growth over the prediction horizon and higher euro-area inflation, to which the ECB reacts with higher interest rates), generates a strong and persistent recession in the Czech economy (*Figure 1*). Such a deep recession, together with increased uncertainty in financial markets, leads in the g3 model to depreciation of the Czech koruna (*Figure 2*), which would increase the inflation pressures. The CNB would react by considerably tightening its monetary policy, as depicted by the spike in the 3M PRIBOR. However, part of the spike is also due to the assumed interbank market freeze as a consequence of the increased uncertainty (*Figure 3*). The resulting inflation would not deviate too much from its baseline path (*Figure 4*). Once the temporary effects of the interbank market freeze and depreciation drop out, the CNB reacts to the protracted recessionary path of GDP, which would otherwise lead to strong deflationary pressures, by cutting interest rates. Although the trajectory for interest rates might look somewhat counterintuitive at first sight, it is consistent with the evolution of the macroeconomy and the assumed risks and is not very different from real developments in periods of financial crisis.

4.2 Data Used

In general, the development of stress-testing frameworks is dependent on the available data sources, which can differ from one jurisdiction to another. This is also why it is difficult to create a unified stress-testing framework. While macroeconomic variables for estimating or calibrating macroeconomic models are usually available, some financial variables, especially the credit risk parameters (PD, LGD), for estimating satellite models for credit risk are not always accessible—at least in sufficiently long time series and for relevant credit portfolios.

The CNB uses several data sources for its stress-testing framework. First, internal supervisory and monetary statistics data—reported usually at monthly frequency by all banks—are used to capture the main features of banks' balance sheets and performance indicators. These data are also used for estimating the satellite models, in combination with other data sources. Second, credit registers are used to obtain the PD (for use in the satellite models). For corporate PDs, the CNB's Central Credit Register is used. It contains all credit granted by Czech banks to individual entrepreneurs and legal entities. This register has been operated by the CNB since November 2002. To obtain the values of default rates, which are used as proxies for PDs in the stress tests, individual loan data are used and the default rate is computed as the volume of loans which become classified as non-performing over a 12-month horizon divided by the volume of loans not classified as non-performing at the beginning of the 12-month period. For household default rates, a credit register operated by a private company in the Czech Republic (the Czech Credit Bureau) is used. The CNB therefore does not have direct access to this data source. However, under a bilateral agreement, data on aggregate newly past due loans have been provided to the CNB quarterly since 2007Q3. This enables us to calculate the aggregate default rate and estimate macroeconomic credit risk models for the household sector.

At the current stage, aggregate banking sector data are used in estimating the satellite models, so the bank-level variability is not utilized. However, we use data on the level of risk (PD) for non-financial corporations by main industries (e.g., agriculture, mining and manufacturing), which results in higher losses for banks that are more exposed to riskier industries. For future research, the satellite models should employ the panel data of all Czech banks to produce bank-specific forecasts that better reflect the interbank heterogeneity.

The rest of the stress-testing framework, however, is based on detailed individual bank data, which enables us to assess particular banks' riskiness stemming from their on- and off-balance sheet structure with respect to the particular scenarios and ad-hoc shocks. This enables us to assess the risk profiles of each bank in the sector. However, the results are published on an aggregated level only, revealing only the number of banks getting close to or under the 8% regulatory limit (and their joint share in the banking sector's assets).

4.3 Satellite Models

The current DSGE and real-business cycle models do not suffice to generate scenarios incorporating financial crises of the post-Lehmann type and the complexities of the financial sector in general. As White (2012) puts it, "all of the models in common use essentially assume linearity, have either no or very primitive financial sectors, and focus on 'flows' of expenditures rather than the buildup of 'stocks' (especially of debt) over time". Within the context of stress testing, the deficiencies of financial sector modeling in current structural macroeconomic frameworks can be partially replaced by satellite models.

The development of satellite models differs from that of common forecasting models in several respects. The first and essential difference is their purpose. While common forecasting involves the prediction of future events given the current information set, satellite models—as an integral part of stress testing—simulate hypothetical events that might potentially happen under a specific set of circumstances subsumed under the headline of a "stress" or "adverse" scenario. A primary concern in this regard relates to the consistency of such scenarios, which usually integrate complex macroeconomic and financial linkages. Nonetheless, the consistency issue will most likely not be fully resolved, given that the conditioning (and partial) macro scenarios they use as a primary input already provide an inaccurate basis for estimation.

The potential conflict between consistency and macroeconomic stress scenarios can be further aggravated when the satellite models involve the estimation of a system of equations (e.g., VAR) modeling macro and financial variables jointly. In particular, the macro relationships estimated in the second phase might be at odds with the macroeconomic links obtained in the preceding scenario development stage. In this sense, the key and daunting task of satellite models within the stress-testing context is to consistently translate (possibly in a reduced form) macro shocks into financial sector variables.

Another major difference between traditional forecasting and satellite models concerns data. Satellite models are limited by the number of available input variables if they are to use consistent macro scenarios. In other words, macro variables that are not included in the first phase of DSGE-driven scenario generation, as well as more disaggregated data at the bank and/or company level, do not enter the satellite models if one hopes to preserve at least a certain level of scenario consistency. Furthermore, the available time series are relatively short, particularly for a country like the Czech Republic. Reliable financial sector series in the Czech Republic start after 2002 (after the previously state-owned banks that dominated the banking sector were privatized and started to behave in a more market-sensitive manner) and thus we need to resort to a combination of time series from different data sources at the cost of additional noise in the data, use a higher (i.e., monthly) frequency or resort to less demanding approaches in terms of degrees of freedom (e.g., single-equation approaches or Bayesian methods).

A final difference from standard forecasting relates to the model selection criteria. Apart from a range of common forecast performance criteria, satellite models evaluate alternative hypothetical scenarios that, irrespective of consistency, simulate events that have not been realized. Models that perform well according to a preferred forecasting metric and/or benchmark scenario might produce unreasonable or even impossible values in the available stress scenario. Furthermore, the high collinearities commonly present in macro data in combination with short time series increase the model's sensitivity to the lag structure. Given the operating horizon for the stress-testing exercise, one might prefer specifications with a shorter lag structure trading off forecast performance with earlier model response.

The satellite models in the CNB use as explanatory variables only those macro variables which are used within the g3 model, but in principle they could also use financial variables which are themselves products of other satellite models or the stress-testing framework itself. In the current framework, the satellite models include models to forecast PD/default rates (credit risk models), credit growth, property prices and pre-provision profit (in the CNB's stress-testing framework adjusted operating profit). In a wider sense, one could also include the yield curve and LGD estimation among the satellite models, as the predictions of these variables are also constructed using predictions of macro (or other satellite models') variables and a certain elasticity. Nevertheless, the LGD "models" are a combination of expert judgment and rather straightforward assumptions: a quarter-on-quarter decline in property prices (in percentage points) transforms into a one-to-one increase in the LGD on mortgages (in percentage points) from an initial level set in line with the available LGD data acquired from banks in the common (bottom-up) stress-testing project (around 20%; see CNB 2009); a difference in the adverse versus baseline path in GDP (in percentage points) multiplied by two is added/subtracted each quarter to the initial value of corporate LGD (45%); a quarter-on-quarter increase in unemployment (in percentage points) multiplied by four transforms each quarter to an increase in LGD on consumer loans from the initial level that the CNB gets from banks (55%). As to the yield curve models, these are based on the no-arbitrage condition (longer-term rates are calculated as compounded expected short-term rates) and a risk premium that is expertly set, as described before.

The general modeling strategy combines an automated general-to-specific model-selection (Gets) algorithm that identifies a subset of potential predictor variables including structural breaks and a quasi out-of-sample forecast metric of all possible combinations of predictor variables from Gets over a pre-specified number of lags. The quasi out-of-sample performance is measured by RMSE on a pre-specified number of periods (quarters). The main motivation for the two-step approach is to pick up variables that have a sound explanatory power in-sample and simultaneously maintain a reasonable forecasting performance (quasi) out-of-sample, especially for the critical out-of-sample period that includes the 2009 economic recession in the Czech Republic. Furthermore, the resulting model should have sound properties over the whole sample so that the final selection is not a mere statistical redundancy.

The relative performance of the Gets algorithm has been discussed extensively in Doornik (2009). The algorithm is an iterative search procedure allowing for tree search and maintaining model congruency throughout the selection process. The Gets approach is thus not path-dependent as many other model-selection procedures are (Hendry, 2009). Importantly, by introducing cross-block estimation (Hendry et al., 2008), the algorithm can handle the case of more variables than observations.

The candidate explanatory variables for individual satellite models are selected based on economic theory. As the *ceteris paribus* clause conditions any theoretical relationship, and our knowledge regarding the rapidly evolving environment of a transition economy is only limited, we further allow for an extended set of variables reaching beyond the standard theories (Hendry and Morgan, 1995).

Both the Gets algorithm and the quasi out-of-sample exercise allow for a wide range of approaches, including the ARIMAX (AutoRegressive Integrated Moving Average with eXogenous variables), ARDL (AutoRegressive Distributed Lag), ARFIMA (AutoRegressive Fractionally Integrated Moving Average) and SETAR (Self-Exciting Threshold AutoRegressive) model classes. Nonetheless, due to computational constraints, each forecast exercise starts with a few of the simplest specifications and only later checks for more demanding alternatives of the ARFIMA/SETAR type.[12] Note that the specifications selected by our two-step procedure might contain a number of imprecisely estimated (i.e., insignificant) variables. These could reflect the underlying structure of the model (e.g., ARDL for credit growth models), strong economic justification (such as the interest rate in default models) or the need to preserve model congruency within the Gets procedure.

Table 1 lists the resulting specifications of the credit risk models for the corporate, consumer and household segments, which are the main segments in the CNB's stress-testing framework.[13]

The credit risk models were estimated within a simple ARIMAX framework. The dependent variables are the three-month default rates of the relevant segment; in the case of consumer loans the dependent variable is the first difference of the three-month default rate.[14] The default rates have been transformed using the logit transformation to address the variables' boundedness within the [0,1] interval.[15] All the underlying level variables (such as GDP) and interest rates (3M Pribor interbank rate) are expressed in real terms unless stated otherwise. *CZK/EUR* denotes the detrended value of the nominal exchange rate and serves as a proxy for the external environment. *Property price QoQ growth* measures the evolution of housing prices on the Czech real estate market.

Given the small sample size and the corresponding high degree of uncertainty, the estimated long-term elasticities should be taken with this in mind. Nonetheless,

[12] Multi-equation approaches with theoretically plausible endogenous variables were likewise considered and compared with their single-equation alternatives. The results do not seem to perform better.

[13] For the remaining loans, the averages of PD and LGD are used. These loans would include loans to non-residents, government and self-employed people.

[14] The reason for taking first differences was the non-stationary behavior of the consumer segment default rate over time.

[15] Other transformations such as inverse Gaussian were considered but did not outperform the logit transform.

Table 1 Credit Risk Models for Individual Segments—Probability of Default (PD)

Corporate			Consumer			Housing		
dependent variable pd_t			dependent variable Δpd_t			dependent variable pd_t		
pd_{t-4}	-0.179		Δpd_{t-3}	0.356	*	pd_{t-1}	0.881	***
	(0.125)			(0.152)			(0.134)	
3M Pribor$_t$	0.014		Δpd_{t-4}	0.055		pd_{t-4}	-0.184	
	(0.073)			(0.157)			(0.103)	
3M Pribor$_{t-1}$	0.057		*GDP*	-4.489	**	*3M Pribor*$_t$	-0.032	
	(0.082)		*QoQ growth*$_{t-2}$	(1.744)			(0.018)	
3M Pribor$_{t-2}$	-0.177	*	*Property price*	0.018	***	Δ*CZK/EUR*$_t$	0.023	
	(0.083)		*QoQ growth*$_{t-4}$	(0.004)			(0.020)	
Δ*CZK/EUR*$_t$	-0.031		*Constant*	-0.009		Δ*CZK/EUR*$_{t-2}$	0.046	*
	(0.087)			(0.020)			(0.020)	
Δ*CZK/EUR*$_{t-2}$	0.085					*GDP*	-0.014	*
	(0.071)					*YoY growth*$_{t-4}$	(0.007)	
GDP	-0.074	***				*Constant*	0.352	*
YoY growth$_{t-4}$	(0.016)						(0.145)	
Constant	1.332	***						
	(0.155)							
N	30		N	30		N	30	
Adjusted R^2	0.435		Adjusted R^2	0.652		Adjusted R^2	0.911	

Source: Authors' calculations

the cumulative impact of GDP growth on default rates is consistently negative in all segments and the cumulative response to the exchange rate depreciation for housing and to property price inflation for the consumer segment is positive, both in line with expectations. On the other hand, the estimated cumulative impact of *3M Pribor* in both the corporate and housing segments, though rather imprecise, goes against the *ex ante* expectations.

Table 2 presents the specifications of the credit growth models for the corporate and household segments. The credit growth models were addressed using the ARDL setup (for more details, see Pesaran and Shin, 1995). A long-term co-integrated relationship was assumed (and tested) between corporate credit, real output and the interest rate (the 3M Pribor interbank rate) in the corporate credit equation. For household credit, *3M Pribor* was replaced by the unemployment rate and augmented by a blip dummy for 2007Q4.

Table 3 presents the satellite model for housing prices.[16] Similar to the satellite models for credit risk, the property price model was estimated within the ARIMAX framework. In the case of property prices, the cumulative responses to shifts in the real GDP growth rate (positive) and the unemployment rate (negative) conform to *ex ante* expectations. On the other hand, the response to a shock in wages is rather imprecisely estimated, with an uncertain overall sign and response significance.

[16] Until 2011, the model for house prices estimated and described in Hlaváček and Komárek (2011) was used.

Table 2 Credit Growth Models for Individual Segments

Corporate dependent variable $\Delta ln\_corp\_credit_t$			**Household** dependent variable $\Delta household\_credit_t$		
$ln\_corp\_credit_{t-1}$	-0.837	***	$household\_credit_{t-1}$	-0.052	***
	(0.110)			(0.009)	
$ln\_3M\ Pribor_{t-1}$	0.245	***	*Unemployment*	1.555	
	(0.048)		$rate_{t-1}$	(7.583)	
$ln\_GDPindex_{t-1}$	2.205	***	$GDPindex_{t-1}$	5.195	***
	(0.286)			(1.029)	
$\Delta ln\_corp\_credit_{t-1}$	-0.198		$\Delta household\_credit_{t-4}$	0.537	***
	(0.114)			(0.105)	
$\Delta ln\_corp\_credit_{t-2}$	-0.34		*ΔUnemployment*	-3.938	
	(0.132)		$rate_{t-1}$	(2.360)	
$\Delta ln\_corp\_credit_{t-3}$	-0.438	***	$\Delta GDPindex_t$	5.888	
	(0.140)			(4.386)	
$\Delta ln\_3M\ Pribor_t$	0.005		*dummy2007Q4*	22.56	***
	(0.008)			(4.254)	
$\Delta ln\_3M\ Pribor_{t-1}$	-0.028		*Constant*	-62.34	***
	(0.010)			(13.284)	
$\Delta ln\_3M\ Pribor_{t-2}$	-0.014				
	(0.011)				
$\Delta ln\_GDPindex_t$	0.001				
	(0.003)				
$\Delta ln\_GDPindex_{t-1}$	-0.01	***			
	(0.004)				
$\Delta ln\_GDPindex_{t-2}$	-0.005				
	(0.004)				
Constant	0.506	*			
	(0.201)				
N	32		N	48	
Adjusted R^2	0.725		Adjusted R^2	0.907	

Source: Authors' calculations

Credit growth as one of potential candidates for forecasting property prices did not pass the variable pre-selection phase based on the Gets algorithm.

As regards adjusted operating profit, a small satellite model (1) is used:

$$\Delta AOP_t = -1.3 + 0.07\Delta YC_{t\text{-}3} + 0.94\Delta NPL_{t\text{-}3} + 8.0MA\_GDP_t + 0.08CAR_{t\text{-}1} \qquad (1)$$

where ΔAOP is annual growth in quarterly AOP volumes, ΔYC is the annual change in the slope of the yield curve (5Y–3M), ΔNPL is annual growth in the volume of NPLs, *MA_GDP* is average nominal GDP growth for the last six quarters, and *CAR* is the capital adequacy ratio. These explanatory variables appear to be economically the most important determinants of interest income (the yield curve slope and NPL

Table 3 Satellite Model for Property Prices

dependent variable Δ*prop_pr*$_t$	
Δ*prop_pr* $_{t-4}$	0.356*
	(0.161)
Unemployment rate $_t$	-1.022*
	(0.463)
GDP QoQ growth $_t$	133.789*
GDP QoQ growth $_{t-1}$	161.033*
	(64.040)
GDP QoQ growth $_{t-2}$	46.775
	(63.525)
GDP QoQ growth $_{t-3}$	-62.42
	(59.635)
Wage QoQ growth $_{t-2}$	0.658
	(0.434)
Wage QoQ growth $_{t-3}$	0.101
	(0.523)
Wage QoQ growth $_{t-4}$	-0.805*
	(0.418)
Constant	7.998*
	(4.220)
N	50
Adjusted R^2	0.388

Source: Authors' calculatio

growth as a proxy for risk margins, as with increasing bad loans banks tighten credit conditions and increase retail rates to compensate for increased risk costs) and non-interest income (nominal GDP growth as a proxy for the volume of financial intermediation). While credit growth could also be used as an explanatory variable, it is largely correlated with GDP growth, so we opted to keep the GDP variable. The lagged capital adequacy ratio is significant at the margin, but we prefer to keep it as it adds to the dynamics in the stress tests: if a bank experiences losses and, as a result, a decrease in capital adequacy, this puts additional pressure on its operating income; the main channel through which this could happen is the interest margin (a bank in difficulties might face deposit outflows and thus needs to increase its deposit rates in order to stabilize its deposit base). However, the most important item affecting the AOP estimate is real GDP growth, which enters the model indirectly through the MA_GDP variable. An analysis of the dependence of AOP on alternative assumptions of real GDP growth shows that a decline in growth of 1 pp leads to a decline in AOP of about 10%.

Modeling adjusted operating profit proved to be a very challenging task, as the Czech data do not allow us to estimate a model in which the profit reacts well to macroeconomic and risk variables, although in theory it should. This was shown, for

Table 4 Key Macroeconomic and Financial Variables in the Individual Scenarios (average for given years)

	Actual value	*Baseline Scenario*			*Europe in Depression*		
	2011	2012	2013	2014	2012	2013	2014
Macroeconomic variables							
GDP (y-o-y %)	1.7	0.0	1.9	3.1	-2.0	-3.2	-2.7
CZK/EUR exchange rate	24.6	24.7	24.3	24.2	25.3	26.5	25.9
Inflation (%)	1.9	3.6	1.5	1.7	3.6	1.3	1.4
Unemployment (%)	8.9	8.8	8.9	8.4	9.3	11.0	11.7
Nominal wage growth (%)	2.9	3.1	4.2	5.0	-0.3	0.4	1.5
Effective GDP growth in euro area (%)	2.8	0.5	1.6	2.1	-0.4	-2.4	-2.8
Credit growth (%)							
Total	6.0	3.2	4.1	6.1	0.2	-3.3	-4.5
Corporations	6.1	4.8	6.1	9.3	-0.3	-5.9	-7.7
Households	5.0	3.6	4.4	6.3	0.6	-2.9	-4.4
Default rate (PD %)							
Corporations	3.1	3.2	2.9	2.5	5.9	6.7	6.0
Loans for house purchase	4.7	4.4	4.5	4.1	6.2	8.2	7.4
Consumer credit	4.7	4.3	4.0	3.6	6.1	7.9	7.8
Loss given default (LGD %)							
Corporations	45.0	45.0	45.0	45.0	49.1	55.1	56.6
Loans for house purchase	22.0	22.5	23.4	22.0	28.0	42.5	44.5
Consumer credit	55.0	55.6	56.0	53.8	57.4	64.1	67.1
Asset markets (%)							
3M PRIBOR	1.2	1.0	1.0	2.1	2.1	1.4	0.6
1Y PRIBOR	1.8	1.5	1.5	2.6	2.3	1.5	0.8
5Y yield	2.7	2.3	2.3	2.9	3.1	3.2	2.9
3M EURIBOR	1.4	0.8	0.8	1.1	2.4	1.3	0.2
1Y EURIBOR	2.0	1.0	0.9	1.2	2.3	0.7	0.4
5Y EUR yield	2.0	0.7	0.7	0.8	1.2	1.2	1.2
Change in res. property prices	-1.8	0.1	1.4	3.5	-10.8	-11.7	0.9
Change in share prices	-10.0	-5.0			-30.0		
Banking sector earnings							
Adjusted operating profit (y-o-y %)	2.4	-12.1	0.2	8.4	-27.0	-22.3	11.6

Source: CNB, CNB calculation.

example, in the crisis period 2008–2010, when GDP declined dramatically, giving rise to credit losses, but the adjusted operating profit actually increased somewhat, as banks managed to reduce their administrative costs and increase their interest margins. Thus, the AOP prediction is based largely on conservative expert judgment, assuming a lower-than-average AOP over the horizon of the stress tests, with the above model giving only initial guidance.

Given the inherent uncertainty in predicting financial variables, whether credit risk, credit growth, property prices, LGD or adjusted operating profit, the model forecasts are often adjusted by expert judgment to reflect all available information about developments in the banking system and ensure a conservative estimate (see Section 5).

Table 4 shows the evolution of the main macro and financial variables (as a result of satellite models) in FSR 2011/2012.

4.4 Credit Risk

Credit risk testing is the most important area of stress testing. This testing is based on the use of PD, LGD and EAD for each of the four main segments of the loan portfolio (corporate, mortgages, consumer loans and other). While PD and LGD come from the satellite or simple elasticity-type models, the third parameter, EAD, is determined as the volume of the non-default part of the portfolio (i.e., excluding non-performing loans) and is influenced mainly by the forecast for credit growth.[17]

An increase in PD and LGD has two main effects on individual banks. First, the expected loan losses (in CZK millions), against which banks will create new provisions of an equal amount and record them on the expenses side of the profit-and-loss statement as impairment losses, are calculated as the product of PD, LGD and EAD for each credit segment and quarter.[18] Total assets are then symmetrically reduced by the amount of these expenses.

While the PD estimates over the horizon are a product of the satellite models, for corporate PD we take into account the industry-level PD at individual banks. So, the initial PD at each bank is a weighted average of the PDs of the individual industries to which the bank is exposed. Changes in the aggregate corporate PD are then applied to changes in the PDs of individual industries (in terms of increase, so that the PDs of all industries increase in line with the aggregate one). This allows us to better reflect the industry composition of banks' corporate portfolios.

The product of PD and the volume of the non-default portfolio form the volume of new non-performing loans (NPLs) for each quarter and in each segment. This allows us to generate the volume of total NPLs in the following eight quarters for each bank, and subsequently for the banking sector as a whole, according to the following equation:

$$NPL_{t+1} = NPL_t + \sum_{i=1}^{4} PD_{t+1,i} NP_{ti} - aNPL_t \qquad (2)$$

where *NPL* are non-performing loans, *PD* is the probability of default, *NP* is the non-default portfolio in the four segments defined above, and a is an NPL outflow parameter (i.e., write-offs or sales of existing NPLs, i.e., the default part of the portfolio). Parameter a is set by expert judgment (using information from banks and estimates

[17] In principle, EAD should also include part of the off-balance sheet items using so-called conversion factors for loan commitments, guarantees and credit lines.

[18] According the relevant CNB decree and IFRS, banks are not required immediately to create provisions exactly equal to expected losses, but rather they must create provisions equal to realized losses, i.e., for new NPLs. However, if the loans are gradually reclassified during the quarter into the NPL (i.e., default) category to the extent predicted by PD, banks will ultimately create these provisions in the originally estimated amount. Also, the Basel II rules require IRB banks to deduct the difference between the expected loss and the amount of provisions from their own funds where this difference is positive.

from the credit register) at between 10% and 20% for all segments, i.e., between 10% and 20% of NPLs are written off/sold each quarter and subsequently disappear from the total volume of NPLs and (gross) assets of the bank.

The credit growth model leads to an estimate of the gross volume of loans in individual segments. Using relation (2) for NPL modeling, this allows us to determine for each bank, and subsequently for the banking sector as a whole, the NPL/ /total loans ratio, a standard indicator of the banking sector's health.

Second, in the case of banks applying the Basel II IRB approach to the calculation of capital requirements for credit risk, the capital requirements (or risk-weighted assets, RWA[19]) for credit risk are a function of PD, LGD and EAD. Given that the largest banks in the Czech Republic apply this approach, this relation is applied to all banks for the sake of simplicity. If a constant non-default portfolio volume, i.e., EAD, was assumed, an increase in PD and LGD would result in an increase in RWA and therefore a decrease in capital adequacy.[20] However, this impact interacts with the forecast of the credit growth model, which usually gives a decline in credit, thus mitigating or eventually even reversing the impact of the higher PDs and LGDs on total RWAs. Given that the satellite model for PD is to be understood rather as a satellite model for the expected default rate (i.e., expected loans that would default over a certain period), while in banks' risk models the PD used to calculate RWAs behaves much more slowly, the PD predictions are smoothed before they enter the IRB formula.

4.5 Market Risk

The macroeconomic scenarios contain a prediction of the evolution of the simplified koruna and euro yield curves (rates with 3M, 1Y and 5Y maturities). A change in interest rates has a direct effect on bank balance sheets mainly in the value of bond holdings.[21] The calculation is based on the estimated duration of the bond portfolios, which is calculated by expert judgment on the basis of more detailed knowledge of the maturity structure. Account is also taken of bond portfolio hedging using IRS (interest rate swaps), which for some banks lessens the impact of interest rate changes.

The quarter-on-quarter change in the CZK/EUR exchange rate is applied to the net open foreign currency position (including off-balance-sheet items), generating either a loss or a profit depending on the sign of the net open position and the direction of the exchange rate change.[22] The risk of other foreign currencies is tested indirectly through the CZK/EUR exchange rate, as it is assumed that the exchange rates of these currencies would change at the same rate vis-à-vis the Czech koruna. This simplification is used because the banking sector's FX exposures in currencies other than the euro are rather small in the Czech Republic.

[19] Risk-weighted assets = capital requirements (in CZK millions) × 12.5.

[20] This channel of the impact of increased PD and/or LGD on banks is one of the main sources of the much criticized procyclicality of Basel II (see Geršl and Jakubík, 2012).

[21] At the same time, however, interest rate changes have an indirect effect on credit risk via their effect on the PD estimate. An additional effect of changes in interest rates is on net interest income, which, however, is captured in the modeling of adjusted operating income.

[22] For example, a positive open foreign currency position and appreciation of the koruna leads to losses.

4.6 Interbank Contagion Risk

Interbank contagion risk is modeled in two selected periods (the fourth and eighth quarters). The test uses data on interbank exposures, with the capital adequacy of individual banks being used to determine their probability of default (PD).[23] As interbank exposures are mostly unsecured, LGD is assumed to be 100%. The expected losses due to interbank exposures are calculated for each bank according to the formula PD×LGD×EAD, where EAD is the net interbank exposure. If these losses are relatively high and will lead to a reduction in the bank's capital adequacy and thus an increase in its PD, there follows another iteration of the transmission of the negative effects to other banks through an increase in the expected losses. These iterations are performed until this "domino effect" of interbank contagion stops, i.e., until the rise in PD induced in one bank or group of banks does not lead to a rise in the PD of other banks. Since the interbank exposures are relatively small, this type of risk does not represent large losses in the final results of the stress-test exercises. This result also holds for the use of gross interbank exposures, capturing the risk that netting arrangements could not be applied (testing of gross interbank exposures, however, was performed only internally).

4.7 Sovereign Risk

Starting in 2010, as a consequence of the escalated sovereign crisis, the stress-testing methodology in the severe scenarios used additional assumptions to incorporate current sovereign riskiness, and 50% impairment of the Czech banking sector's exposures to both governments and private institutions vis-à-vis five indebted EU countries[24] was assumed. Later, in August 2011, the impairment was increased to 100%. Though this assumption might be considered highly adverse, it was used in accordance with the principle of prudent and conservative calibration of risks. The total exposure of the Czech banking sector vis-à-vis these countries was around CZK 28 billion in June 2011 and the banking sector was able to absorb such a loss.

In principle, sovereign risk is a part of market risk in a wider sense, as most of the exposure of Czech banks vis-à-vis the GIIPS/PIIGS countries consists of bonds (both government and private). The calculation of the impact thus comes on top of the market risk calculations, which could already entail some devaluation of bonds due to an increase in foreign long-term interest rates (see below).

At the beginning of 2012, the methodology for testing sovereign risk was revised and a more general methodology of haircuts for particular indebted states was developed. Since then, the adverse scenario assumes haircuts on the government bonds of all EU countries whose government debt exceeds the "Maastricht" limit of 60% of GDP, and not only for the most indebted EU countries.

For FSR 2011/2012, the haircuts of highly indebted countries were set pro rata based on their rating agency ratings as of 10 May 2012 (see *Table 5*). For example, the haircut on nominal accounting exposures to Greece (rated CCC in May 2012) was set at 60% for all bank exposures to that country. The haircut is applied to

[23] The PD values in relation to capital adequacy ratios (CAR) are set by expert judgment as follows: PD = 100% for negative CAR; PD = 25% for CAR between 0% and 5%; PD = 15% for CAR between 5% and 8%; PD = 5% for CAR between 8% and 10%; PD = 0.5% for CAR greater than 10%.

[24] Ireland, Italy, Portugal, Greece and Spain, often referred to as PIIGS or GIIPS.

Table 5 Haircuts on Government Bonds of EU Countries with Public Debt Exceeding 60% of GDP Used in the Stress Tests (%)

Country	Rating 10 May 2012	Haircut based on country's rating in %	Haircut based on country's fundamentals in %
Austria	AA+	4	4
Belgium	AA	7	14
France	AA+	4	11
Germany	AAA	0	6
Cyprus	BB+	35	n.a.
Greece	CCC	60	82
Hungary	BB+	35	31
Ireland	BBB+	25	38
Italy	BBB+	25	31
Malta	A-	21	21
Netherlands	AAA	0	2
Portugal	BB	39	54
Spain	BBB+	25	21
United Kingdom	AAA	0	8

Note: Cyprus is excluded in the "fundamental-based" rating because times series Total debt service as % of GNI was not available for the estimates.
Source: S&P, CNB calculation.

the lowered residual value of the exposures, which is around 30% of the original nominal value in the case of Greek government bonds. This assumption thus implies an additional write-down of Greek claims of 18 pp of the original nominal value and a decrease in the residual value of the exposure from 30% to 12%. The haircuts for Portugal (BB), Hungary (BB+) and Ireland (BBB+) were set at 39%, 35% and 25%, respectively. A zero haircut was set for countries with the highest rating (AAA) reporting government debt of more than 60% of GDP.

While the method described above is based on simple extrapolation based on publicly available ratings, the results are rather similar to the figures based on the fundamentals of particular indebted countries (*Table 5*).[25] These were obtained first by estimating the probability of default (PD) of selected countries based on their fundamental macroeconomic characteristics. The model for the sovereign probability of default (PD) was estimated on a subsample of 37 countries over the period 1980–2005 from Benjamin and Wright (2009). The choice of explanatory variables (mean year-on-year GDP growth over the last four quarters and external debt to GDP; data source: IFS IMF) was largely determined by the existing studies on sovereign default (e.g., Das et al., 2012) and by data availability for the given period and country.

[25] An alternative way of obtaining the expected haircuts of indebted countries is to employ the less volatile implied prices of government bonds. Another option is to use the default rates of non-financial companies from publicly available databases of rating agencies (Moody's, Standard & Poor's and Fitch) and then multiply these values by the assumed LGDs. While the first strategy has been chosen by, for example, Morgan Stanley, an approach based on publicly available ratings was preferred in the EBA EU-wide stress tests in March 2011.

The estimated PDs were then multiplied by the average loss given default (LGD) of 50% for sovereign defaults over the period 1998–2010 as indicated in the study by Cruces and Trebesch (2013). For the purposes of the adverse stress scenario, the haircut estimates were further expertly augmented to account for the worsening fundamentals in economies under the adverse scenario and for the effect of risk spillovers and systemic contagion in the course of the sovereign debt crisis.[26]

Exposures to other AAA-rated countries not listed in *Table 5* are subjected to partial impairments, as the adverse scenarios typically assume considerable growth in yields on EU countries' government bonds. This would manifest itself in a loss of investor confidence and growth in risk aversion not only to indebted EU countries, but also to the Czech Republic. As a result, some impairment of all exposures to EU countries, including exposures to AAA-rated countries, is assumed based on the EUR yield curve.

4.8 Ad-Hoc Risks

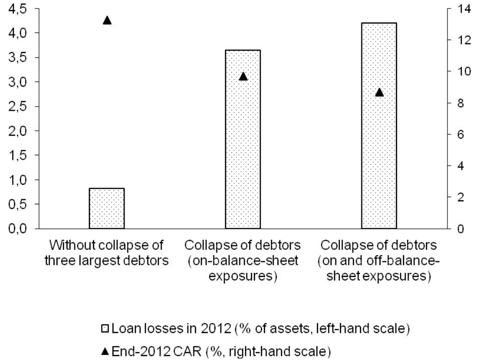
Besides sovereign risk, the stress-testing framework enables us to test specific exposures of interest (ad-hoc risks) which may represent some additional risk in the banking sector. For these exposures, a certain loss rate is assumed. In the past few years, exposures to large developers, some "risky" industries (such as construction and real estate), exporters and solar energy plan investors have been tested, assuming losses of between 50% and 100% of the exposure. Moreover, Czech banks—given their foreign ownership and good liquidity position—have exposures vis-à-vis the groups to which they belong (usually parent banks, but sometimes also foreign sister banks or other banking group members). In FSR 2011/2012, these exposures were also tested, assuming a rather large haircut of 50% (CNB, 2012).

Similarly, a concentration risk test is performed, assuming (as part of the adverse scenario) that the three largest debtors at each bank go into default with a certain loss. The framework takes into account both the current balance-sheet exposure of the largest debtors to the bank as well as the potential increase arising from commitments and guarantees (*Figure 5*, last column). Usually, the test assumes a substantial 80% impairment of total exposures to the largest debtors (but can be changed to another haircut) and causes a significant loss to the sector. In terms of the stress, however, this is clearly an extremely implausible variant which exceeds the level of stress in the stress scenarios normally used owing to its strength and substantially smaller probability. Internally, concentration tests are also performed in other ways, for instance by assuming default of the top X largest borrowers in the banking sector as a whole, which would result in losses for banks exposed to those borrowers.

Finally, the CNB's stress tests also enable testing of a possible write-down of exposures vis-à-vis parent groups. Unlike the majority of CEE banking systems, which have relied on parent bank funding to finance local credit growth, Czech

[26] We proceeded in two steps. First of all, we imposed weaker economic fundamentals on selected economies in the adverse scenario, which led to a roughly twofold increase in PD and haircuts. Secondly, we accounted for cross-country contagion, which was estimated through dynamic correlations between changes in the values of the relevant countries' CDS spreads and the CDS spreads of Greece. The resulting average correlation of 0.55 was multiplied by the change in the value of Greek CDS between September and mid-October 2011. The above-mentioned period was used as a proxy for the increasing contagion from the Greek crisis. The results were added to the original fundamental-driven estimates of the haircuts.

Figure 5 Results of the Concentration Stress Test (Europe in Depression scenario)



Source: CNB, CNB calculation

subsidiaries of Western European banks are usually net creditors rather than net debtors to their parent groups. This entails another type of risk that should be tested, namely the risk of the improbable but plausible scenario of default of some foreign parent banks. In FSR 2011/2012, an impairment of 50% of all so-called adjusted exposures (in principle net exposures, i.e., gross exposures minus liabilities in the form of loans and deposits received from parent banks) of the five largest domestic banks to their parent groups was assumed as a variation of the severe scenario. Similar tests were performed for the Czech banking sector in 2011 jointly with the IMF during the FSAP mission and in February 2012 as part of the CNB's regular quarterly stress testing, where, however, gross exposures were tested. This additional shock should be understood as a means of quantifying the transmission of extreme shocks from parent groups to the Czech banking sector rather than as an assumption that the five parent banks considered will go bankrupt. The impact of such a shock would be quite large, with aggregate capital adequacy approaching the regulatory minimum of 8% in this specific adverse "Europe in Depression" scenario (see CNB, 2012).

4.9 Profit, Regulatory Capital and Capital Adequacy

The stress test assumes that banks will continue to generate revenues even in the stress period, particularly net interest income (interest profit) and net fee income. For these purposes, an analytical item of the profit and loss account called "adjusted operating profit" has been constructed, the main items of which are interest profit plus fee profit minus administrative expenses.[27] The volume of adjusted operating profit for the banking sector as a whole is based on a combination of the prediction by the satellite model (as described above) and expert judgment.

Regulatory capital is modeled in accordance with the applicable CNB regulations. Each bank enters the first predicted quarter with initial capital equal to that

[27] In some CNB Financial Stability Reports this adjusted operating profit was called "net income". Adjusted operating profit is broadly equivalent to the item "pre-provision profit", i.e., operating profit gross of losses on non-performing loans, but differs in that it does not include the impacts of other (interest rate and exchange rate) shocks, whereas pre-provision profit does.

recorded in the last known quarter. If a bank generates a profit in the first predicted quarter (i.e., its adjusted operating profit is higher than its losses due to the shocks), its regulatory capital remains at the same level (is not increased). If, however, it generates a loss, its regulatory capital is reduced by the amount of that loss. The impacts of the shocks are thus reflected in a reduction of capital only if they exceed adjusted operating profit and the bank generates a loss.

It is assumed that those banks which generate a profit for the entire financial year will decide on profit distribution and dividend payments in the second quarter of the following year. Here we assume that each bank, when increasing its capital from retained earnings of the previous financial year, will try to get to its initial capital adequacy ratio if its previous year's profits are sufficient.[28] Depending on the change in RWA, several scenarios are thus possible:

– the bank distributes the entire profit and does not strengthen its regulatory capital (in the event of unchanged RWA);
– the bank uses part of its profit to strengthen its capital and distributes the remainder (in the event of an increase in RWA; however, the entire retained earnings of the previous year will not be needed to reach the initial level of capital);
– the bank uses the entire profit to strengthen its capital (in the event of a relatively sizeable increase in RWA); depending on the size of the increase in RWA, however, it may not reach the original capital adequacy ratio;
– the bank pays dividends that exceed the profit generated (in the event of a decrease in RWA) and thereby also distributes part of retained earnings of previous years.

Total capital adequacy is then calculated for the individual quarters as the ratio of regulatory capital to total RWA. The portion of RWA relating to credit risk is modeled on the basis of the credit risk parameters (see above), while the other components of RWA (or of the capital requirements for other risks) for the individual quarters are determined by expert judgment or kept constant for simplicity.

The total capital adequacy ratio (CAR) is often used as the final variable of the stress tests, as it directly or indirectly includes all the impacts of all the shocks. Moreover, as a main solvency indicator with a regulatory minimum threshold, it is clearly a variable of interest for policymakers within solvency stress testing. *Figure 6* shows the evolution of capital adequacy for the FSR 2011/2012 example.

Given the above rules, banks cannot end up with a CAR higher than the initial level, a reflection of the assumption that banks target the initial CAR level. However, banks might decide to target a different CAR. For example, if the global financial crisis intensifies and the parent banks of Czech subsidiaries become short of capital, they could boost earnings and thus also capital at the parent bank level by paying out larger-than-usual dividends. This would be equivalent to targeting a lower CAR, at least for some time, but given the annual frequency of dividend payout decisions, this could be fixed over the whole horizon of three years. *Figure 7* shows such a simulation, assuming that banks would now target the pre-crisis CAR level, which on

[28] This assumption may not be very realistic at certain times, as banks may decide to pay higher dividends and reduce their capital adequacy ratio below the initial level.

Figure 6 Capital Adequacy Ratio (%)

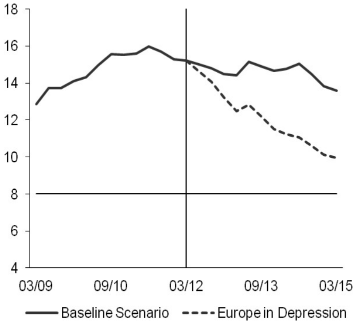
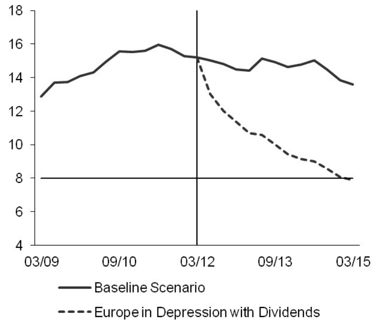


Figure 7 Capital Adequacy Ratio and a One-off Dividend Payout (%)



Source: CNB, CNB calculation.

average equals 12%, rather than the crisis and post-crisis level of around 15% (of course, each bank targets its own pre-crisis level). As the results show, the outflow of dividends can be considered an important additional risk that should be taken into account, as, in combination with the following (maybe unexpected) adverse economic environment within the adverse scenario, banks would be much less resilient given the lower capital buffers with which they would enter the stress period.[29]

In addition to the CAR path, policymakers are usually interested in other capital-related questions, such as how many banks (and which exactly) would be short of regulatory capital and what capital injections are needed to put all banks at least at the minimum CAR of 8%. The CNB dynamic stress-testing framework has this feature, too, and regularly gives this information away in the reports. For example, a typical statement would read:

Although the aggregate CAR is maintained above the regulatory minimum in the scenarios considered, the CARs of 12 banks fall below 8% in the Europe in Depression scenario and those banks would have to strengthen their capital. The necessary capital injections total almost CZK 15 billion, which is around 0.4% of GDP (CNB, 2012, p. 87).

However, given the dynamic quarterly modeling of the banking sector over three years, some caution is necessary when interpreting such a figure. In each of the 12 forecasted quarters, there is a different number of banks with a sub-8% CAR and different capital injections are needed to bring all the banks to the 8% level. In order to be conservative, we take the highest number over the horizon (given the construction of our scenarios and the lags with which the shocks impact the banks, this is usually the last one, as problems accumulate).

5. The Case for Conservative Calibration[30]

We have already mentioned the necessity of prudent (i.e., conservative) calibration and the need to combine the model forecast with expert judgment. In many

[29] The dividend payout assumption was used in the February 2011 CNB stress tests published on the CNB website. Some other central banks have followed the CNB's example. For example, the same risk is tested in the FSR of the Croatian Central Bank (see HNB, 2012).

[30] This part draws heavily on Geršl and Seidler (2012).

cases, the model forecasts are expertly adjusted in order not to underestimate risks. We argue that the whole stress-testing system should be calibrated conservatively in order to take into account the uncertainty related to possible changes in the estimated relationships in the event of adverse economic developments. Hence, ex-post comparison between reality and the predictions generated by the baseline scenarios—such as in the verification exercise performed in 2009—should indicate systematic risk overestimation. In other words, the prediction using the baseline (i.e., likely) scenario should lead to forecasts undervaluing risks compared to those that occur in reality. This is because the whole system should have a "conservative" buffer to offset the uncertainty associated with estimating losses given adverse economic developments, when relations (for example the elasticity between GDP growth and risk parameters such as PD) estimated by standard econometric techniques on data from mainly calm periods can change suddenly for the worse (possible non-linearity of the currently used linear models). This is not only because of the linearity of some of the models employed, but also because of the fact that even non-linear models can underestimate the impact of very adverse economic developments on a particular financial variable. Being prudent in stress testing is in line with the general macro-prudential approach adopted by policymakers and supervisors worldwide, and erring on the conservative side is preferred to possible underestimation of the losses and capital needs of banking systems in crisis, which can have large negative effects on public budgets, on general public perceptions of banks and back onto the economy.

One dimension of prudent calibration is the decision on whether to set shocks to the banking system as a result of models estimated using available data or to set the parameters expertly. Clearly, if the data are not sufficiently long and do not include stress periods, the estimated satellite models might not be well suited for stress-testing purposes. On the other hand, for macro stress tests one needs a link between macroeconomic developments and risk factors for banks. Thus, there is a clear trade-off in terms of having all risk factors estimated via models and the possibility of accumulating a large number of errors, which could underestimate the real impact of shocks on the banking system. The option that was selected in the CNB stress-testing framework reflects this trade-off and uses models only for those factors which can be reasonably modeled, with the view that over time, as better and longer data series become available, other factors currently estimated to a large extent by expert judgment could be predicted via models. This approach was addressed, for example, by BCBS (2012) using quintile regression to assess the tails of the loss distribution.

The conservative buffer can be imposed in a number of ways, such as applying a conservative add-on to the central predictions (such as adding one standard deviation of the dependent variable), using a prediction from a "conservative" confidence interval, using estimates from a quintile regression (e.g., conditional forecasts of the peripheral 10% quintile), or estimating the elasticity on different sub-samples and taking the most conservative one (usually one estimated over a crisis period if such a period is available). Another possibility is to define some variables (such as the PD) in a conservative way[31] or, for parameters set expertly, just using a very conservative setting.

The case for conservative calibration can be illustrated by a simple exercise which uses the data for the Czech economy and assumes the authority (the CNB)

Figure 8 The Adverse Scenario (Real GDP Growth in %, Coincides with the Observed Outcome) (%)

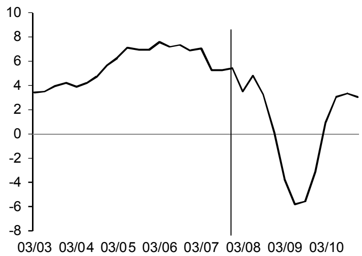
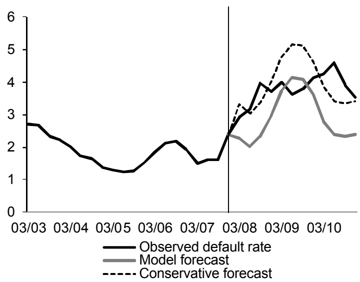


Figure 9 Forecasted Versus Observed Corporate Default Rate (12M Default Rate in %)



Source: Authors' calculations.

running a stress test in early 2008, focusing on forecasting credit losses from corporate portfolios of Czech banks for an adverse scenario. A standard approach would be to estimate the relationship between a credit risk parameter, say the corporate (one-year) default rate, and macroeconomic fundamentals (such as GDP growth), using all available data, which as at early 2008 cover the period 2003–2007 (quarterly data).[32] This relationship would be used to forecast the default rate over the period of the next three years, the current forecasting horizon of the CNB's stress tests, i.e., for the "crisis" period of 2008–2010. If we design the adverse scenario to equal the observed macroeconomic path (a decline in GDP of roughly 4.5% in 2009), we can directly validate the forecast by comparing it to a stress scenario.

A simple OLS-type model was estimated to link the corporate default rate and GDP growth in the Czech Republic using quarterly data (other variables proved insignificant).[33] The prediction using the adverse "2008–2010 crisis" scenario correctly indicates the increase in the default rate and its subsequent decrease due to the economic recovery (*Figure 8*). However, mainly due to the fact that the model was estimated over a calm period of economic growth, the model underestimates the real outcome (*Figure 9*). As can be seen from the comparison, the observed default rate picked up much earlier than forecasted and started to fall much later. The error is quite high—assuming for simplicity a constant corporate portfolio, the model predicts that over the period 2008–2010, 8.8% of the portfolio would default, while in reality the figure was 11.2%.

[31] For example using a definition of PD that is based on the 30+ days in arrears definition of the default rate, which is generally higher than the standard Basel 90+ days definition. However, given the results of the backtesting as to the large overestimation of credit losses—see later in the text—the CNB changed to the standard 90+ definition of the default rate in June 2010 (CNB, 2010). Currently, the conservative margin is safeguarded via an add-on to the predicted PD.

[32] The 12M default rate for corporate exposures is calculated from the CNB credit register, which started operating in late 2002.

[33] The estimated model looks as follows: default rate = 2.99 + -0.2*GDP growth. No lags were identified as significant, partly due to the fact that the default rate is calculated as forward looking, i.e., we are linking, for example, GDP growth in 2006Q1 with the 2006Q1 default rate, which is calculated over the 4-quarter period 2006Q1–2006Q4. This is a simplified model used to illustrate the point. However, it captures the most important effect, namely, the one from GDP.

Thus, a conservative calibration is needed to properly account for the losses, which were higher than predicted. An ex-post analysis shows that the estimation of the equation over the crisis period would lead to a higher elasticity between GDP and the default rate and would predict higher default rates. Since policymakers do not have the crisis-period data before the crisis, an alternative must be used. If we apply a conservative add-on of one standard deviation of the corporate default rate (which equals roughly 1%), the forecasted path is still different (*Figure 9*). However, as it is at a higher level—the three-year impact (three-year default rate) now amounts to 11.9%, much closer to (and even slightly higher than) the observed rate of 11.2%.

An alternative to somewhat arbitrary add-ons of a certain number of standard deviations would be to use techniques that explicitly focus on periods of high stress. Schechtman and Gaglianone (2012) suggest using quantile regression, which associates movements in macro and credit risk variables only in a certain (adverse) quantile of the distribution (see also Koenker and Xiao, 2002).

To conclude this section, the requirement for conservative calibration implies that stress-test prediction errors should be evaluated differently from the errors of standard macroeconomic predictions, where deviations in either direction are regarded as "equally bad". In stress testing, it is appropriate to apply an asymmetric view and tolerate prediction errors toward some overestimation of the risks.

6. Conclusion

This paper has described the current stress-testing framework for testing the resilience of banks in the Czech Republic. The stress-testing framework as a whole is built on the official CNB projection model of DSGE type (g3), a number of satellite models and the dynamic linkages of the models, allowing banks' balance sheets to be modeled at quarterly frequency over a period of three years. A number of ad-hoc shocks and a considerable level of expert judgment are equally important components of the CNB's stress tests. The gradual development of the CNB's stress-testing methodology over the last ten years is discussed to illustrate the main challenges in stress testing and how these challenges, including those brought about by the global financial crisis and the European debt crisis, might be tackled. Even though the models have recently undergone significant improvements, given the experience of the global financial crisis as well as the discussion on the role of stress testing in current macroprudential policy, the stress-testing framework will be further developed in the future.

The main lessons from the development of robust and well-functioning stress tests are as follows:

First, the framework must be calibrated conservatively, as the estimated elasticities in satellite models may change significantly for the worse when risks materialize. Conservative calibration of stress tests ensures that the impact of shocks on the banking sector will not be underestimated in the event of adverse developments.

Second, the assumed shocks should be harsh enough to capture low-probability, high-impact events. This relates both to the calibration of macroeconomic shocks in alternative scenarios and to various ad-hoc shocks, such as defaults by large borrowers or losses on large exposures to parent banks or sovereigns.

Third, the framework must be continuously updated and improved to reflect new data availability, longer time series and new possible risks emerging, judging from the evolution of bank exposures. A regular backtesting exercise assessing the accuracy and robustness of the stress-test models and assumptions should be an integral part of a good framework.

Fourth, the solvency stress-testing framework should ideally become more and more interlinked in a consistent manner with the liquidity stress-testing framework, reflecting the side-effects of both solvency and liquidity (see Geršl et al., 2011; CNB, 2012).

Finally, the stress tests should be actively used in policy and the results regularly published and discussed by professional analysts, as they are an important communication tool and help manage economic expectations. While there is an ongoing general discussion on the role of stress testing in macroprudential policy (Borio et al., 2012; Ong and Čihák, 2010), the experience of the CNB supports the view that central banks should be relatively open and transparent also in this area.

APPENDIX

Satellite Models Estimated in Early 2010 and Used in FSR 2009/2010 and FSR 2010/2011

The corporate default rate was explained by changes in the interest rate, changes in real investment growth, changes in real foreign demand growth, changes in real GDP growth, and real consumption growth (see *Table A1*; the lag is in quarters and ψ denotes the cumulative normal distribution function). Model 1 suggests that lagged increases in interest rates,[34] lagged decreases in real investment growth, lagged decreases in real foreign demand growth, lagged decreases in real gross domestic product growth, and lagged decreases in real consumption growth all positively affect the default rate. It captures domestic demand (real consumption) as well as foreign demand for firms' products (real foreign demand). Real investment can serve as an indicator of firms' financial health, as corporations will probably reduce their investment during times of financial distress. Finally, real GDP was used as a proxy for firms' revenues and the interest rate represented the financial costs of corporate sector funding.

Equation A1:

$$df_t = \psi \begin{pmatrix} c + \beta_1 \left(ir_{t-3} - ir_{t-5} \right) + \beta_2 \left(i_{t-3} - i_{t-8} \right) + \beta_3 \left(fd_{t-2} - fd_{t-6} \right) + \\ + \beta_4 \left(gdp_{t-3} - gdp_{t-8} \right) + \beta_5 gc_{t-7} \end{pmatrix}$$

The Czech household default rate was explained by lagged real GDP growth, changes in the unemployment rate, lagged nominal wage growth and changes in the interest rate—see the following equation A2 and *Table A2*, where the lag is in quarters and ψ denotes the cumulative normal distribution function.

Equation A2:

$$df_t = \psi \left(c + \beta_1 gdp_{t-4} + \beta_2 \left(u - u_{t-1} \right) + \beta_3 w_{t-1} + \beta_4 \left(r_{t-3} - r_{t-4} \right) \right)$$

[34] The 3M PRIBOR (Prague Interbank Offered Rate) is employed.

Table A1 Macroeconomic Credit Risk Model for the Czech Corporate Sector

Description of variable corresponding to estimated coefficient	Notation	Estimate	Standard error	*Pr>|t|*
Constant	c	-2.36400	0.024450	<.0001
Change in interest rate (β_1)	ir_{t-3} - ir_{t-5}	0.14450	0.016770	<.0001
Change in real investment growth (β_2)	i_{t-3} - i_{t-8}	-0.00780	0.000919	<.0001
Change in real foreign demand growth (β_3)	fd_{t-2} - fd_{t-8}	-0.00774	0.001925	0,0004
Change in real GDP growth (β_4)	gdp_{t-3} - gdp_{t-8}	-0.07326	0.006097	<.0001
Real consumbtion growth (β_5)	c_{t-7}	-0.03013	0.005618	<.0001

Note: The lag length is in quarters.

Table A2 Macroeconomic Credit Risk Model for the Czech Household Sector

Description of variable corresponding to estimated coefficient	Notation	Estimate	Standard error	*Pr>|t|*
Constant	c	-2.12680	0.014510	<.0001
Real GDP growth (β_1)	gdp_{t-4}	-0.02832	0.003036	<.0001
Change in unemployment (β_2)	$u_t - u_{t-1}$	0.01238	0.004372	0.009
Nominal wage growth (β_3)	w_{t-1}	-0.01214	0.000816	<.0001
Change in interest rate (β_4)	r_{t-3} - r_{t-4}	0.03398	0.007440	0.0001

Note: The lag length is in quarters.

REFERENCES

Aikman D, Alessandri P, Eklund B, Gai P, Kapadia S, Martin E, Mora N, Sterne G, Willison M (2009): Funding Liquidity Risk in a Quantitative Model of Systemic Stability. *Bank of England Working Paper*, no. 372.

Alessandri P, Gai P, Kapadia S, Mora N, Puhr C (2009): Towards a Framework for Quantifying Systemic Stability. *International Journal of Central Banking*, 5(3):47–81.

Andrle M, Hlédik T, Kamenik O, Vlček J (2009): Implementing the New Structural Model of the Czech National Bank. *Czech National Bank Working Paper*, no. 2/2009.

Bank of England (2009): The Role of Macroprudential Policy. *Bank of England Discussion Paper*, November 2009.

Basel Committee on Banking Supervision (BCBS) (2012): Models and Tools for Macroprudential Analysis. (Bank for International Settlements), *Basel Committee on Banking Supervision Working Paper*, no. 21.

Benjamin D, Wright M (2009): Recovery Before Redemption? A Theory of Delays in Sovereign Debt Renegotiations. (Centre for Applied Macroeconomic Analysis, Crawford School of Public Policy, The Australian National University) *CAMA Working Paper*, no. 2009-15.

Borio C, Drehmann M, Tsatsaronis K (2012): Stress-testing Macro Stress Testing: Does It Live Up to Expectations? *BIS Working Paper*, no. 369.

Breuer T, Jandacka M, Rheinberger K, Summer M (2009): How to Find Plausible, Severe and Useful Stress Scenarios. *International Journal of Central Banking*, 5(3):205–224.

Brunnermeier M, Crockett A, Goodhart C, Persaud A, Shin H (2009): The Fundamental Principles of Financial Regulation. *Geneva Reports on the World Economy*, no. 11.

Buncic D, Melecky M (2013): Macroprudential Stress Testing of Credit Risk—A Practical Approach for Policy Makers. *Journal of Financial Stability*, 9(3):347–370.

Čihák M (2005): Stress Testing of Banking Systems. *Finance a úvěr-Czech Journal of Economics and Finance*, 55:418–440.

Čihák M, Heřmánek J (2005): Stress Testing the Czech Banking System: Where Are We? Where Are We Going? *Czech National Bank Research and Policy Notes*, no. 2005/02.

Čihák M, Heřmánek J, Hlaváček M (2007): New Approaches to Stress Testing the Czech Banking Sector. *Finance a úvěr-Czech Journal of Economics and Finance*, 57:41–59.

Committee of European Banking Supervisors (CEBS) (2009): *Guidelines for Stress Testing*.

Cruces J, Trebesch C (2013): Sovereign Defaults: The Price of Haircuts. (American Economic Association) *American Economic Journal: Macroeconomics*, 5(3):85–117.

Czech National Bank (CNB) (2008): *Evaluation of the Fulfilment of the CNB's Inflation Targets 1998–2007*.

Czech National Bank (CNB) (2009): *Financial Stability Report 2008/2009*.

Czech National Bank (CNB) (2010): *Financial Stability Report 2009/2010*.

Danmarks Nationalbank (2010): *Financial Stability 2010*.

Das U, Papaioannou M, Trebesch C (2012): Sovereign Debt Restructurings 1950–2010: Literature Survey, Data, and Stylized Facts. *IMF Working Paper*, no. 12/203.

Doornik JA (2009): Autometrics. In: Castle JL, Shephard N (Eds.): *The Methodology and Practice of Econometrics: Festschrift in Honour of David F. Hendry*. Oxford, Oxford University Press.

Drehmann M (2009): Macroeconomic Stress Testing Banks: A Survey of Methodologies. In: Quagliariello G (2009): *Stress Testing the Banking System: Methodologies and Applications*. Cambridge University Press.

European Banking Authority (EBA) (2011): *Overview of the EBA 2011 Banking EU-wide Stress Test*.

Financial Stability Board (FSB) (2011): *Macroprudential Policy Tools and Frameworks, Report on the G20*.

Foglia A (2009): Stress Testing Credit Risk: A Survey of Authorities' Approaches. *International Journal of Central Banking*, 5(3):9–46.

Franta M, Baruník J, Horváth R, Šmídková K (2011): Are Bayesian Fan Charts Useful? An Evaluation of Macroeconomic Forecasts and Financial Stability Stress Tests. *International Journal of Central Banking*, forthcoming.

Geršl A, Heřmánek J (2008): Indicators of Financial System Stability: Towards an Aggregate Financial Stability Indicator? *Prague Economic Papers*, (2):127–142.

Geršl A, Jakubík P (2012): How Important Is the Adverse Feedback Loop for the Banking Sector? *Ekonomický časopis* [Slovak Journal of Economics], 60(1):32–49.

Geršl A, Komárková Z, Komárek L (2011): Models for Stress Testing Czech Banks' Liquidity Risk. *Czech National Bank Working Paper*, no. 11/2011.

Geršl A, Seidler J (2010): Stress Test Verification as Part of an Advanced Stress-Testing Framework. In: Czech National Bank: *Financial Stability Report 2009/2010*, pp. 92–101.

Geršl A, Seidler J (2012): How to Improve the Quality of Stress Tests through Backtesting. *Finance a úvěr-Czech Journal of Economics and Finance*, 62(4):325–346.

Gorton G (2009): Information, Liquidity, and the (Ongoing) Panic of 2007. *American Economic Review*, 99:567–572.

Haldane A (2009): *Why Banks Failed the Stress Test*. (Paper presented at the Marcus Evans Conference on Stress-Testing, 9–10 February 2009)

Hamerle A, Liebig T, Scheule H (2004): Forecasting Credit Portfolio Risk. (Deutsche Bundesbank Research Centre) *Discussion Paper Series 2: Banking and Financial Studies*, no. 01.

Hendry DF (2009): The Methodology of Empirical Econometric Modelling: Applied Econometrics Through the Looking-Glass. In: Mills T, Patterson K (Eds.): *Palgrave Handbook of Econometrics, Volume 2: Applied Econometrics*.

Hendry DF, Johansen S, Santos C (2008): Automated Selection of Indicators in a Fully Saturated Regression. *Computational Statistics*, 33:317–335.

Hlaváček M, Komárek L (2011): Regional Analysis of Housing Price Bubbles and Their Determinants in the Czech Republic. *Finance a úvěr-Czech Journal of Economics and Finance*, 61(1):67–91.

Hrvatska Narodna Banka (HNB) [Croatian National Bank] (2012): *Financial Stability Report No. 9* (July 2012).

International Monetary Fund (2012): *Czech Republic—Publication of Financial Sector Assessment Program Documentation—Technical Note on Stress Testing the Banking Sector.* IMF, July 2012.

Jakubík P, Heřmánek J (2008): Stress Testing of the Czech Banking Sector. *Prague Economic Papers* (3):195–212.

Jakubík P, Schmieder C (2008): Stress Testing Credit Risk: Is the Czech Republic Different from Germany? *Czech National Bank Working Paper*, no. 9/2008.

Jakubík P, Sutton G (2011): Thoughts on the Proper Design of Macro Stress Tests. In: Bank for International Settlements (ed.): *Macroprudential Regulation and Policy*, 60:11–119.

Koenker R, Xiao Z (2002): Inference on the Quantile Regression Process. *Econometrica*, 70(4):1583–1612.

Majnoni G, Martinez Peria M, Blaschke W, Jones M (2001): Stress Testing of Financial Systems: An Overview of Issues, Methodologies, and FSAP Experiences. *IMF Working Paper*, no. 01/88.

Moody's (2009): Approach to Estimating Czech Banks' Credit Losses. *Moody's Global Banking*, July 2009.

Norges Bank (2010): *Financial Stability 1/2010.*

Oesterreichische Nationalbank (2010): *Financial Stability Report 19.*

Ong L, Čihák M (2010): Of Runes and Sagas: Perspectives on Liquidity Stress Testing Using an Iceland Example. *IMF Working Paper,* no. 10/156.

Pesaran MH, Shin Y (1995): An Autoregressive Distributed Lag Modelling Approach to Cointegration Analysis. (Faculty of Economics, University of Cambridge) *Cambridge Working Papers in Economics*, no. 9514,

Schechtman R, Gaglianone WP (2012): Macro Stress Testing of Credit Risk Focused on the Tails. *Journal of Financial Stability*, 8(3):174–192.

Schmieder C, Puhr C, Hasan M (2011): Next Generation Balance Sheet Stress Testing. *IMF Working Paper*, no. 11/83.

Seidler J, Jakubík P (2009): Estimation of Expected Loss Given Default. In: *Czech National Bank: Financial Stability Report 2008/2009*, pp. 102–109.