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By Jérôme Henry
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In 2013 all ECB publications feature a motif taken from the €5 banknote.

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CONTENTS

LIST OF ABBREVIATIONS

AFS	Available for sale
AIRB	Advanced internal rating based approach
CEBS	Committee of European Banking Supervisors
CRD II	Directive 2006/48/EC and 2006/49/EC as amended by the Directive 2009/111/EC
CRD III	Directive 2010/76/EU
CRD IV	Directive 2013/36/EU of the European Parliament and of the Council of 26 June 2013 on access to the activity of credit institutions and the prudential supervision of credit institutions and investment firms, amending Directive 2002/87/EC and repealing Directives 2006/48/EC and 2006/49/EC
CRR	Regulation (EU) No 575/2013 of the European Parliament and of the Council of 26 June 2013 on prudential requirements for credit institutions and investment firms and amending Regulation (EU) No 648/2012
DTA	Deferred tax assets
EAD	Exposure at default
EBA	European Banking Authority
ECB	European Central Bank
EU	European Union
FIRB	Foundation internal rating based approach
HFT	Held for trading
HTM	Held to maturity
LGD	loss given default
PD	Probability of default
P&L	Profit and loss
RWA	Risk-weighted assets
SSM	Single Supervisory Mechanism

ABSTRACT

The use of macro stress tests to assess bank solvency has developed rapidly over the past few years. This development was reinforced by the financial crisis, which resulted in substantial losses for banks and created general uncertainty about the banking sector's loss-bearing capacity. Macro stress testing has proved a useful instrument to help identify potential vulnerabilities within the banking sector and to gauge its resilience to adverse developments.

To support its contribution to safeguarding financial stability and its financial sector-related work in the context of EU/IMF Financial Assistance Programmes, and looking ahead to the establishment of the Single Supervisory Mechanism (SSM), the ECB has developed a top-down macro stress testing framework that is used regularly for forward-looking bank solvency assessments. This paper comprehensively presents the main features of this framework and illustrates how it can be employed for various policy analysis purposes.

JEL Classification: C53, D85, E37, E44, E47, E58, G01, G21, G28.

Keywords: macro stress test, systemic risk, financial crisis, banking sector, macro-prudential policy, micro-prudential supervision.

EXECUTIVE SUMMARY [1]

The financial and sovereign debt crises have highlighted how important it is for banks to have solid capital buffers that enable them to withstand extreme and unexpected shocks to their balance sheets and thus ensure that they can act as effective financial intermediaries even in periods of turbulence. A macro stress-testing framework is often used to assess in a forward-looking manner the resilience of the banking sector to (adverse) macroeconomic and financial developments. In line with its responsibility for safeguarding financial stability in the euro area, the ECB also employs macro stress-testing tools in its regular macro-prudential assessments. Furthermore, macro stress testing will be an integral part of the ECB's activities in relation to its future role as a single bank supervisor for the euro area.

This paper provides a comprehensive and detailed description of the analytical framework employed by the ECB in a top-down manner for macro stress testing of banks' solvency. This work is done to support its contribution to safeguarding financial stability and its financial sector-related work in the context of EU/IMF Financial Assistance Programmes, and to challenge results from bottom-up stress tests conducted by banks and their supervisors. Furthermore, the stress-testing framework can be used for both micro and macro-prudential purposes once the ECB takes up its supervisory powers in the context of the establishment of the Single Supervisory Mechanism (SSM). The paper is structured as follows:

Chapter 1 of this paper reviews the motivations for conducting macro stress tests and briefly summarises the recent institutional history in terms of who conducts macro stress tests at the global and European levels. Finally, it surveys the main objectives and challenges that stress testers face and that need to be considered when constructing an analytical framework for macro stress testing purposes.

Chapter 2 presents the bank solvency analysis framework developed and used at the ECB for top-down macro stress testing purposes. The framework consists of four pillars; namely, the macro-financial scenario design, models to translate scenarios into impacts on banks, the solvency calculation module, and a module for contagion and feedback analysis. The framework is thus based on a number of different building blocks and models that are linked together consistently and dynamically to provide a flexible tool for assessing banking sector resilience against identified systemic risks.

The stress testing tool is employed for different purposes and in various contexts. Chapter 3 provides illustrative examples and descriptions for how the framework is used in regular financial stability analysis and also how the tool can be used in the context of challenging results from bottom-up stress tests.

Chapter 4 concludes.

1 Prepared by Jérôme Henry and Christoffer Kok

I INTRODUCTION[2]

To measure the resilience of the entire financial system against severe yet plausible adverse scenarios, macro stress tests link macro-financial variables with the health of financial institutions. The system-wide nature of macro stress tests also reflects the use of a macroeconomic adverse scenario, which can cover several risk factors, unlike a sensitivity analysis where the health of a financial institution or of the financial system is checked against specific risk factors and in isolation from the other parts of the financial system.

The use of macro stress tests to assess bank solvency has developed rapidly over the past few years. This development was reinforced by the financial crisis, which resulted in substantial losses for banks and created general uncertainty about the banking sector's loss-bearing capacity. Macro stress testing has proved a useful instrument to help identify potential vulnerabilities within the banking sector and to gauge its resilience to adverse developments.

To support its contribution to safeguarding financial stability more broadly[3] and its financial sector-related work in the context of EU/IMF Financial Assistance Programmes, the ECB has also developed a macro stress testing framework that is used regularly for forward-looking bank solvency assessments.[4] Moreover, the importance of stress testing within the ECB will be reinforced by the establishment of the Single Supervisory Mechanism (SSM), which will require tools to identify vulnerable banks both from a bank level (micro-prudential) and a system-wide (macro-prudential) perspective.

Against this background, the aim of this Occasional Paper is to comprehensively present the main elements of the current analytical infrastructure developed at the ECB for conducting macro stress tests. The publication therefore aims at providing a reference point for the risk assessment analysis conducted by the ECB in the various policy contexts mentioned above.

This introductory chapter presents the main drivers behind the increasingly widespread use of macro stress tests to assess bank solvency and introduces the main features of stress tests. It also briefly reviews how macro stress tests can be used to assess and possibly respond to systemic risk, and how they can be used by central banks in pursuance of their macro-prudential responsibilities. In subsequent chapters, the paper then presents the various building blocks of the analytical framework used by the ECB for bank solvency analysis (Chapter 2) and provides an illustration of how the tool is used in practice for systemic risk assessments and in relation to cross-checking of bottom-up results (Chapter 3). Chapter 4 concludes.

1.1 WHY CONDUCT MACRO STRESS TESTS?

Next to the prime responsibility for monetary policy, the responsibility for helping to safeguard financial stability features prominently in the mandate of the ECB, as well as of several other central

2 Prepared by Patrizia Baudino, Inês Cabral, Markus Kolb, Matthias Sydow and Dawid Żochowski.

3 The concept of financial stability has been defined by the ECB as "*a condition in which the financial system is capable of withstanding shocks and the unravelling of financial imbalances*". See ECB *Financial Stability Review*, June 2010, Special Feature B, "Analytical models and tools for the identification and assessment of systemic risks", for an overview of tools for risk surveillance and assessment.

4 While this paper focuses primarily on bank solvency stress testing, it should be noted that bank liquidity stress is dealt with by the ECB via its lender of last resort function.

banks.[5] This task requires the systematic review of possible sources of risk to the financial system that are of a potential systemic nature and the assessment of their potential magnitude. The latter implies an evaluation of the impact should these risks materialise. The monitoring of risks and the assessment of their severity are thus complementary for the detection of systemic risks.[6]

Macro-prudential oversight and policies aim at limiting systemic risk or instances of widespread instability in the financial system. This is opposed to micro-prudential oversight, which focuses on institutions individually to ensure their soundness as single entities. Macro stress testing models, which can be employed to assess the impact on the financial sector of the materialisation of identified risks, have become the workhorse of analytical tools for macro-prudential risk assessments and are the backbone of central banks' systemic risk assessment tools. These exercises constitute a key tool in regular risks assessments, notably as part of the regular macro-prudential oversight process at a national or supranational dimension.

Macro stress tests of bank solvency are conducted to support macro-prudential oversight and are generally conducted in a centralised fashion, i.e. they are top-down stress tests. As explained in more detail in the following chapters, the results' degree of precision depends greatly on the quality and granularity of the information available, notably on individual financial institutions and their inter-linkages with other parts of the financial system.

Such top-down exercises are different from the supervisory stress tests conducted for micro-prudential purposes, which assess individual institutions' ability to withstand shocks, typically using tailor-made scenarios/sensitivity analysis. The tests are conducted under supervisory guidance by the supervised entities.

A middle-ground approach is represented by coordinated exercises whereby the same macro-financial baseline and adverse scenarios are given to all participating entities along with strict methodological guidance – as in the case of exercises conducted by the European Banking Authority (EBA). The aim of such exercises is typically to estimate the capital needs of individual banks and for the banking sector overall, which is why they are usually referred to as bottom-up stress tests. Top-down stress tests can play an important role in benchmarking the results from system-wide bottom-up stress tests in the context of peer review processes.

Given its system-wide focus, macro-prudential analysis goes beyond assessing the direct impact of shocks to entities individually and their magnitude in aggregated terms. It must also account for spill-over within the banking sector and possible contagion effects between banks and other financial sectors.[7] Furthermore, systemic risk assessment requires the analysis of interactions between the financial system and the real economy, supported by macro-financial models (see section 2.5).

5 In the euro area, this responsibility is conferred to the European System of Central Banks (ESCB) by Article 127 (5) of the Treaty on the Functioning of the European Union – *"The ESCB shall contribute to the smooth conduct of policies pursued by the competent authorities relating to the prudential supervision of credit institutions and the stability of the financial system",* as well as by Article 25 (1) of the ESCB Statute. Furthermore, the Council Regulation on the Single Supervisory Mechanism confers upon the ECB the task of supervising euro area banks one year after the entry into force of the regulation, which therefore reinforces the role of the ECB in prudential supervision.

6 Systemic risk can be defined as the risk that financial instability would become so widespread that the functioning of a financial system would be impaired to the point where economic growth and welfare would suffer materially. See ECB *Financial Stability Review*, December 2009, Special Feature B, "The Concept of Systemic Risk", for a characterisation of systemic risk from an analytical and research perspective.

7 Bilateral relations in the economy are notoriously concentrated in the financial system; see e.g. evidence by Castrén and Kavonius (2009) using euro area financial accounts.

1.2 WHO CONDUCTS MACRO STRESS TESTS?

The use of stress tests from a macro-prudential perspective is closely related to the lessons from the financial crises over the past decade. Among the forerunners, the IMF launched the regular use of macro stress tests in the context of its Financial Assistance Assessment Programs in the aftermath of the Asian financial crisis in the late 1990s. Although financial crises had occurred before, the Asian crisis provided a striking example of instability in the financial sector spreading quickly and pervasively across several countries, even though macroeconomic fundamentals had appeared to be very strong prior to the crisis. It therefore triggered a new focus on assessing financial system conditions from a systemic perspective, as opposed to looking only at individual financial firms.

Since then, the use of stress tests to address systemic risk has deepened, following the recent financial crisis in the US and Europe. In these two cases, the use of macro stress tests has been expanded from being a tool to regularly monitor and assess financial sector conditions to being a tool to respond to the crisis. In both the US and the EU, stress tests became part of the policy toolkit for crisis management by the relevant national authorities.[8] In the US, there was the Supervisory Capital Assessment Program (SCAP), in 2009;[9] the EU had EU-wide stress test exercises, with associated extensive disclosure of risk exposures, in 2010 and 2011.[10] At the individual country level in the EU, another example of the use of stress tests in crisis times is offered by the macro stress tests that have been conducted in the context of programmes of economic and financial assistance to crisis-affected European countries (see Section 3). Moreover, some national authorities already used macro stress tests to monitor and assess the resilience of their banks, independently of EU-wide initiatives, in part also as a result of the experience gained under IMF Financial Sector Assessment Programs (FSAPs).[11]

As the most acute phase of the recent financial crisis has receded, the emphasis in the EU and the US has started to shift to using stress tests under normal circumstances, to address systemic risk *ex-ante*.

In the US, legislative initiatives have established the need for the regular conduct of two sets of stress tests; i.e., the Comprehensive Capital Analysis and Review (CCAR) and Dodd-Frank Act (DFA) stress tests. Both are run by the Federal Reserve and in both cases the aim of the authorities is to ensure that financial institutions have robust capital planning processes and adequate capital. The CCAR, which is conducted annually, is closer in scope to micro stress tests: when the Federal Reserve deems an institution's capital adequacy or internal capital adequacy assessment processes unfavourable under the CCAR, it can request it to revise its plans to make capital distributions, such as dividend payments or stock repurchases. Closer in scope to macro stress tests, DFA stress tests in turn are forward-looking exercises conducted by the Federal Reserve and financial companies regulated by the Federal Reserve. The DFA stress tests aim to ensure that institutions have sufficient capital to absorb losses and support operations during adverse economic conditions.

8 See ECB *Financial Stability Review*, December 2010, Special Feature A for a discussion of the use of stress tests during a crisis.

9 See Board of Governors of the Federal Reserve System (2009) and Bernanke (2013).

10 The European Banking Authority was established by Regulation (EC) No. 1093/2010 of the European Parliament and of the Council of 24 November 2010. The EBA officially came into being as of 1 January 2011 and has taken over all existing and ongoing tasks and responsibilities from its predecessor, the Committee of European Banking Supervisors (CEBS). In particular, concerning stress testing, the CEBS launched the first EU-wide stress test in 2009. In 2010, CEBS enhanced its stress testing exercise by starting to disclose bank-level results rather than only aggregate, EU-wide results.

11 For a review of country experiences and related references, see ECB *Financial Stability Review*, December 2010, Special Feature A, as well as the following section for selected references.

In the EU, the regular conduct of EU-wide stress tests has been envisaged from the start in the legislation setting up the European Systemic Risk Board (ESRB) and the three European Supervisory Authorities (ESAs), namely the European Banking Authority (EBA), the European Insurance and Occupational Pensions Authority (EIOPA) and the European Securities and Markets Authority (ESMA), all of which started operating in 2011. Of the three ESAs, the EBA has made the most extensive use of stress tests, partly because of the greater urgency of addressing weaknesses in the European banking sector, and partly due to the fact that the practice and theory of stress testing for banks is relatively more developed than the tests for insurance companies or markets and financial market infrastructures.[12] Bank-level results of EU-wide stress tests were published by the EBA in 2011 (and by its predecessor, the CEBS, in 2010). Banks were required to gradually increase their capital buffers to the minimum level enforced under the exercise, either from market sources or with public backstops. The EBA did not conduct a stress testing exercise in 2012, owing to its 2011 launch of two overlapping initiatives to address bank solvency, which it completed in mid-2012 (i.e. the 2011 stress test and the Capital Exercise[13] of late 2011). The timeline of the EBA's next round of EU-wide stress testing, expected in 2014, has been adjusted by the EBA so that the exercise will be conducted once supervisors have completed asset quality reviews, according to the EBA recommendation.[14] The expanded timeline is also expected to allow optimal coordination between the EBA and the SSM's activities, and in particular the comprehensive balance sheet assessment to be conducted by the ECB in the lead-up to the launch of the SSM.

According to the legislation establishing the ESAs and the ESRB, the ECB is expected to provide analytical support to the ESRB, which in turn cooperates with the ESAs in their EU-wide stress testing exercises. Up to now, major components of the analytical support by the ECB (to the EBA in particular) have included adverse macroeconomic scenarios, technical methodological input (such as the calculation of benchmark parameters for credit and market risk) and its top-down stress test, which has been provided in the context of a peer review for the EU-wide stress testing exercise for banks.[15]

Finally, macro stress tests have also been used in the context of EU/IMF programmes of economic assistance to troubled euro area countries. In a number of cases, the ECB staff's stress test results have been used to cross-check and, if necessary, to challenge the results from external consultants or from national authorities (see Section 3). These comparisons have generally enhanced the robustness of the results.

Going forward, as macro-prudential mandates expand the competencies of central banks, macro stress tests will continue playing a crucial role in shaping the credibility of micro- and macro-prudential supervision. In the EU, an important step will be the new institutional set-up associated with the launch of the Single Supervisory Mechanism (SSM) and its wide-ranging micro and macro-prudential tasks, including the power to carry out assessments of credit institutions of the participating Member States as part of its regular activity, and also, initially, to assess their situation at the moment when the SSM will assume operational responsibilities.

12 Of the other two ESAs, EIOPA has also conducted stress tests since its inception in 2011, but disclosed only aggregate results in a summary format. The ECB publishes a forward-looking risk assessment of insurance companies in the semi-annual *Financial Stability Review*, based on publicly available data (see Box 5 for further details about stress tests for insurance companies). The ESA responsible for markets and infrastructures (ESMA) has not yet conducted publicly disclosed EU-wide stress tests.

13 The Capital Exercise is not a stress test, as it did not rely on an adverse macroeconomic scenario. However, it was a solvency assessment exercise, as it required that banks assess their capital buffers against a common minimum capital threshold. For this reason, the Capital Exercise exhibited a very strong overlap with what a stress test exercise would have been in 2012.

14 See the EBA Press Release of 16 May 2013, "*EBA recommends supervisors to conduct asset quality reviews and adjusts the next EU-wide stress test timeline*".

15 In addition to this, the ECB also provides substantial statistical support to the ESRB and the ESAs; see for example ECB (2013).

1.3 THE MAIN OBJECTIVES AND CHALLENGES OF MACRO STRESS TESTS

Notwithstanding the role they have assumed in macro-prudential analysis by central banks, it must also be recognised that macro stress tests have important limitations. Stress tests are, in particular, not appropriate early warning indicators, as emphasised for example by Borio et al. (2012). While macro stress tests were an effective crisis management and resolution tool in the recent crisis, the authors also criticise macro stress tests for missing the build-up of risks on banks' balance sheets in the run-up to the current crisis. Furthermore, most stress testing models have difficulty capturing the typically non-linear nature of systemic risks or macro feedback loops, and they fail to adequately reflect counterparty and liquidity risks. Notably, many macro stress testing frameworks are still largely partial equilibrium exercises (Summer, 2007) that do not account for feedback loops arising from banks' (and market participants') behavioural responses to the imposed shocks.[16] In addition, they do not account for disruptive spirals between market and funding risk, all of which lie at the centre of financial instability (Brunnermeier, 2009; Gorton and Metrick, 2009). Furthermore, as argued by Greenlaw et al. (2012), macro stress test scenarios should consider both sides of the balance sheet, and explicitly consider fire sales, runs by wholesale creditors, common exposures and credit crunch risks. Acharya et al. (2012) furthermore argue that simple market-based estimates outperform capital shortfalls identified in recent macro stress tests in the US and EU.[17]

In order to overcome these limitations, researchers and the central banking community have recently made considerable efforts to further improve macro stress testing frameworks. Traditionally, top-down stress tests have assessed the resilience of the system as a whole against macro-financial adverse developments, primarily by focusing on credit risk, i.e. the link between macro variables, probabilities of defaults (PDs) and loss given defaults (LGDs) in banks' portfolios. Therefore, liquidity risk, funding risk, counterparty risk, vicious fire sales or macro feedback loops were captured only to a limited extent. However, recently more efforts have been made to include such dynamics. The most prominent examples include Elsinger et al. (2006), who were among the first to develop a stress testing framework that integrates credit, market, interest rate and counterparty risks using credit register and interbank claim data. Similarly, the Bank of England's RAMSI framework (Aikman et al., 2009; Alessandri et al., 2009; Burrows et al., 2012) incorporates, on top of all relevant channels, feedback mechanisms capturing counterparty credit risk in the interbank market and feedback channels arising from market and funding liquidity risk. In a reduced form vector autoregressive model, Jacobsen et al. (2006) link macro and balance sheet-specific factors with companies' default frequencies, which allows the model to evolve dynamically in response to macro factors. Finally, in the EBA stress tests of 2011, market risk embedded in banks' sovereign books portfolios was also tested against an adverse scenario, which to some extent accounted for the vicious feedback loop between sovereigns and their banks prevailing at the time of the stress test. As will be shown in the subsequent sections, the ECB's analytical framework also incorporates many elements that address some of the identified shortcomings.

16 See also He and Krishnamurthy (2012), who likewise stress the partial equilibrium limitation of traditional stress tests and offer a modelling framework for linking stress test results with the probability of a financial crisis occurring (against which to assess the severity of the stress test).

17 They argue that the Marginal Expected Shortfall (MES), which identifies the capital shortfall of financial firms in severe market-wide downturns, outperforms huge stress tests mainly on account of risk-weighted assets (which give a capital subsidy to those banks holding what have turned out to be the riskiest assets in the European exercise). In the authors' view, such market-based measures need to act as a complement to stress tests even if a "through the cycle" view is adopted, as market prices at which private funding is accessed are critical for the banks' survival.

These advances notwithstanding, macro stress testing tools remain works in progress and, especially, are still largely partial equilibrium in nature, unable to fully and consistently capture the dynamic interactions between different agents in an economy exposed to adverse shocks. Significant challenges persist in combining the macro perspective with the micro elements at the bank level and accounting for feedback effects between these different perspectives. By definition, macro stress testing analysis is an attempt to analyse how conditions in the banking sector are affected by and interrelate with conditions in (and shocks to) the macroeconomic and financial environment. Ideally, therefore a general equilibrium perspective should be pursued to properly take into account all the feedback mechanisms between the banking sector and the real economy in a consistent and dynamic manner. However, top-down stress testing frameworks (including the one presented in this paper) use at best partial equilibrium approaches. The main reason is that stress testing frameworks at their core are focused on deriving individual and heterogeneous bank level results, which is difficult to process within fully consistent general equilibrium frameworks that typically operate with a representative agent concept. With current modelling techniques, the latter could at best be analysed from the perspective of the aggregate banking sector level. It is, however, not sufficient to analyse the top-down stress test results at the level of the aggregate banking sector. Individual banks will react differently to specific shocks depending on their business model. Hence, to ensure accurate stress test results, input is needed at the bank (and portfolio) level.

Indeed, the relevance and accuracy of any stress-test exercise relies on the underlying data input (see also Box 2). First, data availability defines the extent to which the exercise can cover various aspects of banks' risk profile. This is particularly important when top-down stress tests are used to challenge the results of the bottom-up exercises, where an adverse scenario feeds banks' internal models. Ideally, both exercises should rely on the same datasets, albeit in practice data limitations often severely constrain the capacity of top-down stress tests to cover individual banks' exposures. In this regard, high-granularity data on banks' balance sheet and off-balance sheet positions, as well as profit-and-loss accounts, are also of the essence for macro stress tests.

Furthermore, while the ECB's stress testing framework is primarily attuned to forward-looking solvency assessments, analytical tools for carrying out liquidity/funding risk assessment are also important for completing a macro-prudential analysis toolkit (see also Box 6 for a review). This notwithstanding, even the forward-looking solvency assessment can be carried out taking into account liquidity and funding shocks and thus to some extent capture the impact of liquidity stresses. It is also worth noting that while this paper focuses primarily on bank solvency stress testing, the top-down macro stress testing framework can also be tailored to systemic risk analysis of other types of financial institutions (see for instance Box 4 for a description of a top-down insurance sector solvency stress testing tool). Finally, in light of the macro-prudential policy mandate entrusted to the ECB in the Single Supervisory Mechanism, the development of macro-prudential tools to assess the impact of specific macro-prudential policies will be essential.[18] The macro stress testing framework will also be useful in this regard (see also Box 4).

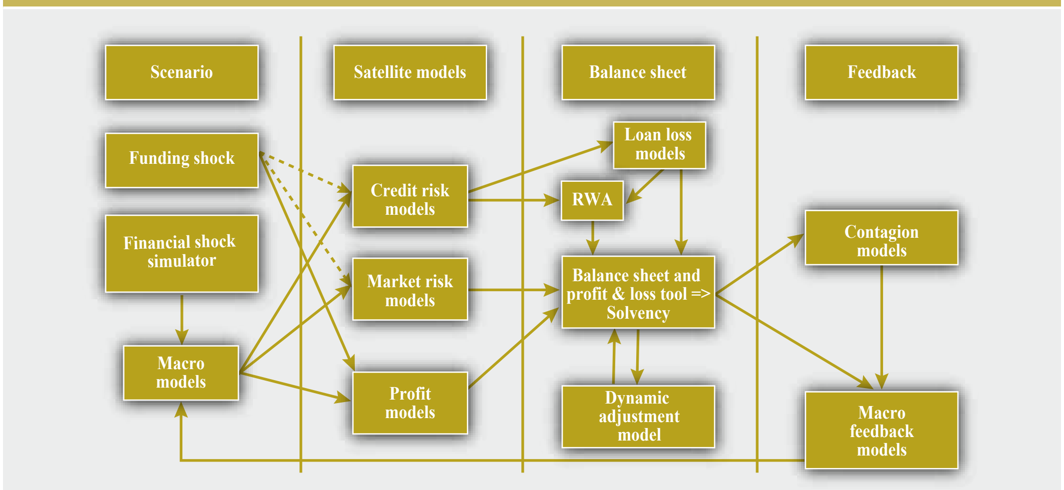
18 See also ECB Financial Stability Review, May 2013, Special Feature A on "Exploring the nexus between macro-prudential policies and monetary policy measures".

2 SOLVENCY ANALYSIS FRAMEWORK – THE FOUR PILLARS[19]

Forward-looking bank solvency analysis, or (top-down) macro stress testing, especially when carried out using individual bank level information, requires a number of different but interrelated analytical steps. The ECB's solvency analysis framework reflects this approach and can broadly be described as a modular system with a four-pillar structure (see Chart 1): The *first pillar (scenario design)* consists of the design of the macro-financial scenarios to be imposed on the banking sector; the *second pillar (top-down satellite models)* in turn consists of the modules used to translate the scenarios into variables affecting the valuation of bank balance sheet components and banks' loss absorption capacity; the *third pillar (balance sheet module)* takes the projected profit and losses derived from the satellite models to individual bank balance sheets with the aim of calculating the resulting impact on each bank's solvency positions. Finally, the *fourth pillar (feedback modules)* takes the analysis beyond the first-round impact on bank capitalisation to assess what could be the derived second-round effects of the initial bank solvency impact in terms of contagion within the financial system and in terms of feedback effects to the real economy. This chapter describes in detail each of the modules underlying the four-pillar forward-looking solvency analysis framework in place at the ECB.

For presentational purposes, in this chapter and in Chapter 3, the various building blocks of the framework are illustrated on the basis of a common baseline and a common adverse scenario. The baseline scenario is the European Commission Spring 2013 Forecast, which implies EU average real GDP growth of -0.1% in 2013 and 1.4% in 2014. The adverse scenario reflects risks related to *bank profitability linked to credit losses and a weak macroeconomic environment* – materialising through negative shocks to aggregate demand and aggregate supply in a number of EU countries – and *risks of renewed tensions in euro area sovereign debt markets due to low growth and slow reform implementation* – materialising through an increase in long-term interest rates and declining

Chart 1 The four pillar structure of the ECB solvency analysis framework



Source: ECB.
Note: "RWA" refers to risk-weighted assets.

19 Prepared by Adrien Amzallag, Maciej Grodzicki, Marco Gross, Grzegorz Hałaj, Christoffer Kok, Markus Kolb, Miha Leber, Matthias Sydow, Cosimo Pancaro and Angelos Vouldis.

stock prices. The adverse scenario would result in EU average real GDP growth rates of -2.0% in 2013 and 0.8% in 2014 and also embeds shocks to long-term sovereign bond yields ranging from 0 to 330 basis points across EU countries, as well as to national stock price indices ranging from -1% to -36%. The starting point for the analysis is bank balance sheets as of the fourth quarter of 2012, and the scenario covers two years up until end-2014.

2.1 MACRO-FINANCIAL SCENARIO DESIGN

The "first pillar" of the framework, and the starting point of the analytical chain ultimately leading to a forward-looking assessment of banking sector capitalisation, is the macro-financial scenario design module. The process of designing an appropriate (adverse) macro-financial scenario broadly consists of two steps. First, on the basis of the main systemic risks identified as pertinent at a given juncture, these risks will need to be mapped to scenario building blocks that correspond to the general story-line that the stress tester is aiming to capture (see Section 2.1.1). Second, once the scenario building blocks have been defined and expressed as exogenous shocks to specific variables representing the relevant risk factors, the impact of these shocks on the wider macroeconomic and financial environment needs to be quantified using relevant modelling techniques (see Section 2.1.2).

2.1.1 MAPPING RISKS TO SCENARIOS

The general starting point for any stress testing exercise, be it top-down or bottom-up, is a set of macro-financial risks that could have a bearing on the resilience of the banking system (or other financial institutions being stressed).

At the ECB, the identification and monitoring of systemic risks is derived from its regular financial stability surveillance exercises, which apply a wide range of systemic risk indicators and early warning models for this purpose. Typically, the financial stability surveillance analysis will provide a list of 3-5 main systemic risks that are deemed particularly pertinent at a given juncture.

On the basis of this list of key risks, the ECB carries out a systemic risk assessment to gauge the impact of their materialisation on the resilience of the financial system and its ability to support the real economy.

The ECB approach to mapping risks to scenarios is characterised by a number of important elements:

- First of all, in keeping with the purpose of creating sufficient stress on the financial institutions, the scenarios should reflect severe but plausible outcomes. In other words, when designing the scenarios, due consideration needs to be given to ensuring a level of severity that is appropriate (i.e. having a sufficiently strong impact on the banks) but not implausible (i.e. it should reflect a material risk). Typically, the severity is defined in probabilistic terms both as regards the initial shocks to input variables (e.g. bond yield shocks; see Section 2.1.2) and as regards the impact on key macro output model variables (e.g. real GDP growth).

- For practical as well as communication reasons, the design process is usually based on various scenario building blocks that match specific risks to the extent possible. Focusing on individual risks is useful for the calibration of exogenous shocks reflecting particular risks, which in a second step are input into the models generating the scenarios. In some exercises the solvency analysis is then conducted for each of these scenario blocks with the aim of assessing the isolated impact of specific risks on the financial sector's soundness. In other exercises, the aim is to create one comprehensive adverse scenario which encompasses all risks considered.

- While the general approach to scenario design is to create scenario building blocks matching specific risks, it has to be kept in mind that some risks may not be orthogonal to each other, as the underlying factors behind them may be mutually reinforcing. Hence, a shock calibrated to reflect one particular risk could be expected to also have spillover effects on the calibration of other interrelated risks. For example, in recent years some of the key systemic risks surrounding the euro area financial system have been the risk of sovereign contagion and the risk of bank funding constraints. However, a typical sovereign contagion scenario would be based on shocks to sovereign bond yields, which in turn, via the adverse feedback loop between sovereigns and domestic banks, could be expected to also have direct implications for bank funding costs. From this perspective, a joint shock calibration of the two risks makes more economic sense.

- Another important point is that different types of risks may require different types of macro-financial models for scenario generation. Some macroeconomic models may be well-suited to generating scenarios based on shocks to real economic variables (such as consumption, investment, external trade, etc.) but may be less suited to handling shocks of a more financial nature, shocks with non-linear effects that are difficult to capture with standard macro models or shocks requiring a well-specified real-to-financial feedback loop. For this reason, the ECB macro scenario design module applies an eclectic approach when selecting models to produce scenarios. In other words, there is no reliance on one particular model. Instead, the model selection is tailored to the specific risks that the scenario (building block) is supposed to reflect. Against this background, the next sub-section describes the range of macro-financial models and shock generation tools that are most often applied in the context of the ECB's forward-looking bank solvency analysis.

2.1.2 MACRO-FINANCIAL MODELS USED TO CALIBRATE SHOCKS AND PRODUCE SCENARIOS

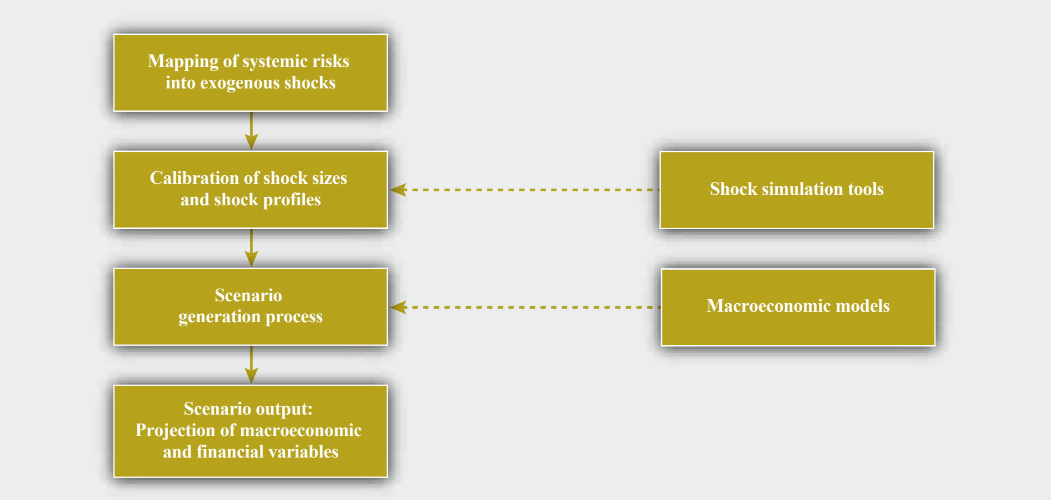
The starting point for the macroeconomic scenario generation is the set of exogenous shocks that, as mentioned in the previous section, should reflect the underlying systemic risks to be analysed (see Chart 2). Following the mapping of systemic risks into exogenous shocks, various shock simulation tools are employed to determine the relevant shock sizes and profiles. In the next step, using the calibrated shocks as inputs, the macro-financial scenario is generated by relevant macroeconomic models. The output of these models is a projected path for a broad range of country-specific macro-financial variables.

The shock profile of these inputs to the scenario generation process can be calibrated in a number of ways. From a conceptual point of view, for the calibration of shock sizes and shock profiles, at least three strategies are conceivable:

1) Ad-hoc calibration without recourse to any model or historical distribution of risk factors. Instead, the shock size calibration could be based on movements in the relevant economic or financial variable observed over past crisis episodes.

2) Shock size calibration based on historical distributions: Even without employing a 'model', historical distributions can serve as a guide to calibrating shock sizes. For example, the historical distributions of stock prices can be used to compute a 1% Value-at-Risk measure for a subset or the entirety of markets under scrutiny.

Chart 2 A schematic overview of the scenario generation process



Source: ECB.

3) Shock size calibration based on shock distributions, with shocks being inferred from a dynamic model: Models produce the fit, and the resulting residuals, i.e. the portion of variation in the model variables that the model cannot explain, are interpreted as shocks. Those shocks can be calibrated using the size and distribution of the corresponding model residuals.

For financial shock simulation purposes in particular, the second approach is usually preferred in the risk assessment analysis. The main reason for operating with an approach, which does not rely on a pre-defined model specification (i.e. it is "non-parametric"), is that scenarios often require shocks to many financial variables that are strongly interrelated. Such large scale multivariate distributions (of say 40-50 different financial market variables) are difficult to treat analytically (i.e. parametrically), so a non-parametric approach is typically preferred.

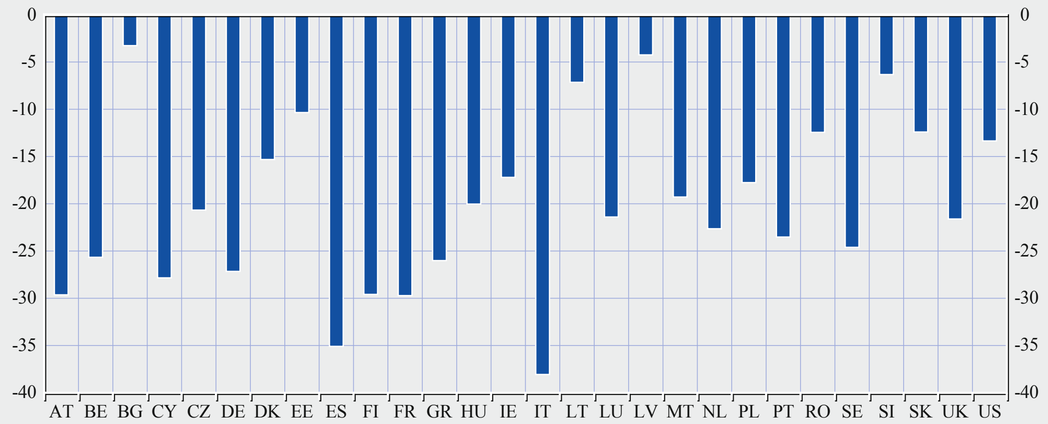
As an example of the approach, it is assumed that shocks originate simultaneously in four European stock and bond markets (eight shock origins in total).[20] The dependence of all other stock markets and long-term interest rates contained in the model is captured by a *copula*,[21] whose functional form is left unspecified (a 'nonparametric' approach). Also, the distributions of the individual markets (the 'marginal' distributions) are left unspecified. Charts 3 and 4 show the shock profiles for stock prices and long-term interest rates resulting from the eight originating shocks. This profile has been generated based on a daily data sample of stock prices and 10-year government bond yields for 28 EU countries and the US, with a forward horizon of 60 business days (1 quarter). For stock prices (Chart 3) a substantial dispersion in the simulated shock sizes is observed, with declines ranging from -3% in Bulgaria to -38% in Italy.

20 For example, to reflect sovereign debt contagion effects. The shock sizes are usually determined using the historical distribution of the variable to be shocked by setting a specific percentile threshold, e.g. 1% or 5%, for the probability of occurrence. The shock-originating countries in the presented example were Belgium, Spain, France and Italy.

21 A "copula" is a distribution function which describes the dependence between random variables. Technically speaking, the cumulative distribution function of a random vector can be written in terms of marginal distribution functions and a copula. The marginal distribution functions describe the marginal distribution of each component of the random vector, whereas the copula describes the dependence structure between the components and thereby 'couples' the marginal distributions to a joint distribution. For a general description of copulas, see for example Nelsen (1999).

Chart 3 Shocks to stock prices (at T=0)

(percentages)



Sources: Bloomberg and ECB calculations.

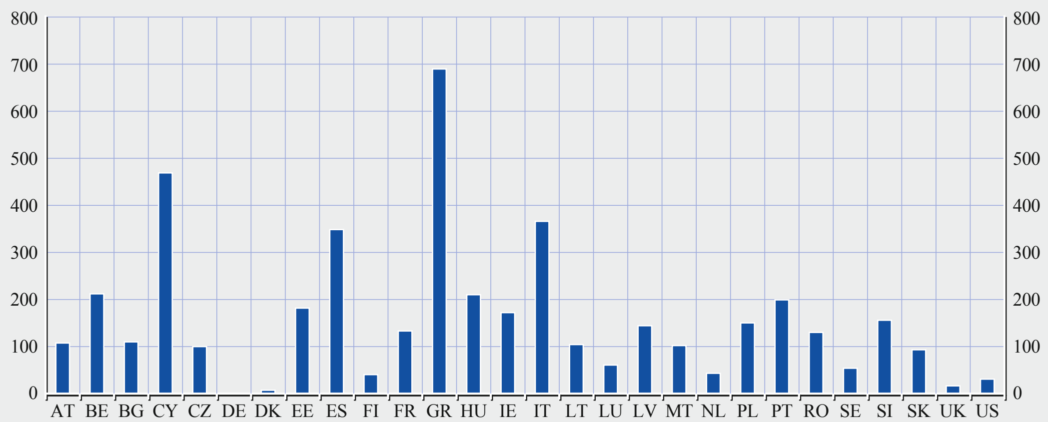
For the long-term interest rate shocks (Chart 4), bond yields were simulated as spreads to the German bond yield. Consequently, in this case the level of the bond yield for Germany was assumed to be unaffected. Also, the simulated shocks to long-term interest rates display a notable dispersion (Chart 4), with increases ranging from 0% in Germany to 690 basis points in Greece.

Once relevant shock profiles reflecting underlying systemic risks have been calibrated, they are input to the relevant dynamic macro-econometric models. A variety of models useful for generating stress test scenarios are available at the ECB.

Many of the models regularly applied for forward-looking solvency analysis purposes have been developed mainly to support monetary policy. One modelling package, which has been developed

Chart 4 Shocks to long-term interest rates (at T=0)

(basis points)



Sources: Bloomberg and ECB calculations.

(at the ECB) with a specific stress test scenario generation view in mind, is called 'Stress-Test Elasticities' (STEs). The STE platform combines National Central Banks' models into a multi-country EU-wide simulation tool, which allows simulating exogenous shocks (to real economic variables and some financial asset prices) to derive responses for a wide range of endogenous model variables covering each of the 28 EU countries.[22] In total, the STE output encompasses 50-60 macroeconomic and asset price variables. Another important feature is that the STEs also incorporate intra-EU trade spillovers. Hence, imposing a shock to one country using the STEs is also likely to have real economic implications for the projected macroeconomic outlook in other EU countries.

For shocks reflecting risks to the EU external environment, scenarios are often based on the NiGEM model, which is a large-scale estimated multi-country/-regional macroeconomic model with global reach.[23] To calibrate international spillover effects (of, for instance, stock price or bond yield shocks), NiGEM can be complemented with a global VAR (GVAR) model.[24] A typical output of NiGEM when employed for stress testing purposes is the impact on EU external demand from some imposed shock to the global environment. These EU external demand shocks are then in turn input to the STEs to derive the resulting real economic implications across the EU countries.

Whereas the STEs is the most directly applicable scenario simulation tool for stress testing purposes, other ECB macro models have some comparative advantages to the STEs. The latter, for example, are less well suited with respect to generating scenarios where the initial shocks should reflect some real-financial amplification mechanism (e.g. shocks to borrowers' collateral values, such as property price declines, leading to tighter borrowing constraints) or where the shocks should reflect risks emanating from within the financial sector itself (e.g. funding constraints, loan supply effects, etc.). For such purposes, use is often made of more structural models with explicit real-financial linkages, such as the dynamic stochastic general equilibrium models of Darracq Pariès et al. (2011) and Christiano et al. (2010). While these models better capture financial sector and real economy interlinkages already at the scenario generation stage, their main limitation is that the range of output variables from these models is somewhat more limited than what is provided by the STEs.

The final step of the scenario generation process is the output of the employed macroeconomic models based on the initial exogenous shocks imposed. As a purely illustrative example, Charts 5 and 6 show the deviations of real GDPs and price inflation over a twelve quarter horizon, expressed as percentage deviations from baseline levels (expressed in annual terms), in response to the asset price shocks described above. The shocks on stock prices and long-term rates were assumed to be permanent.

The charts illustrate a common feature pertaining to euro area-wide (and EU-wide) exercises, namely that the severity of any adverse macroeconomic scenario is likely to display substantial cross-country heterogeneity. For example, a relatively muted impact on real GDP and inflation is observed in countries such as Germany, Denmark, France and Poland, whereas effects are

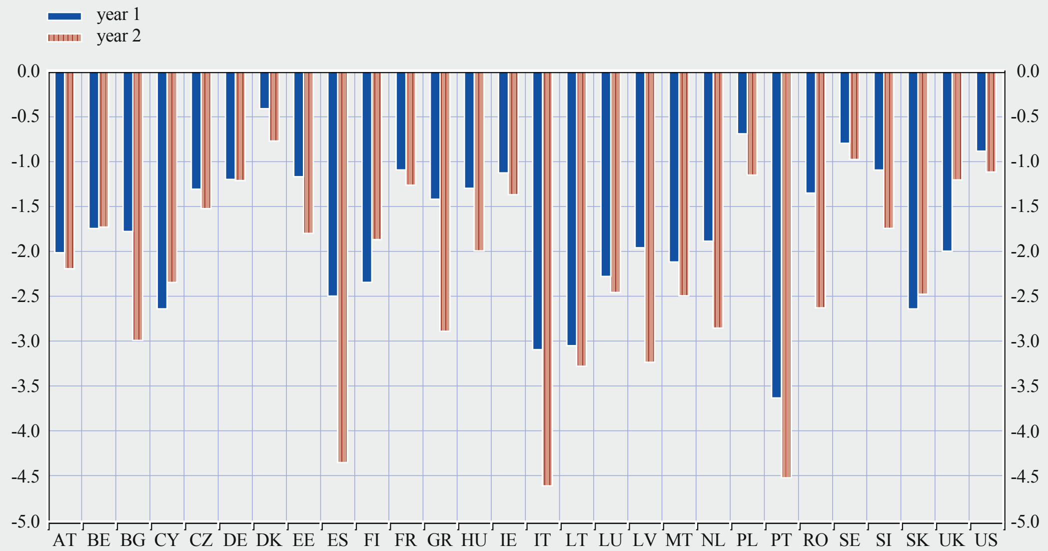
22 The design of the tool follows that of the Projection Updated Elasticities (PUEs) that are regularly used for scenario purposes in the Eurosystem macroeconomic projection process. Similar to PUEs, STEs are based on impulse-response functions of endogenous variables to pre-defined exogenous shocks. These partial multipliers are derived from the National Central Banks (NCBs) models.

23 NiGEM was developed by the UK-based National Institute of Economic and Social Research (NIESR).

24 For details on the GVAR model, see Dees et al. (2007).

Chart 5 Cross-country scenarios for real GDP (two-year horizon)

(percentage deviation from baseline levels)

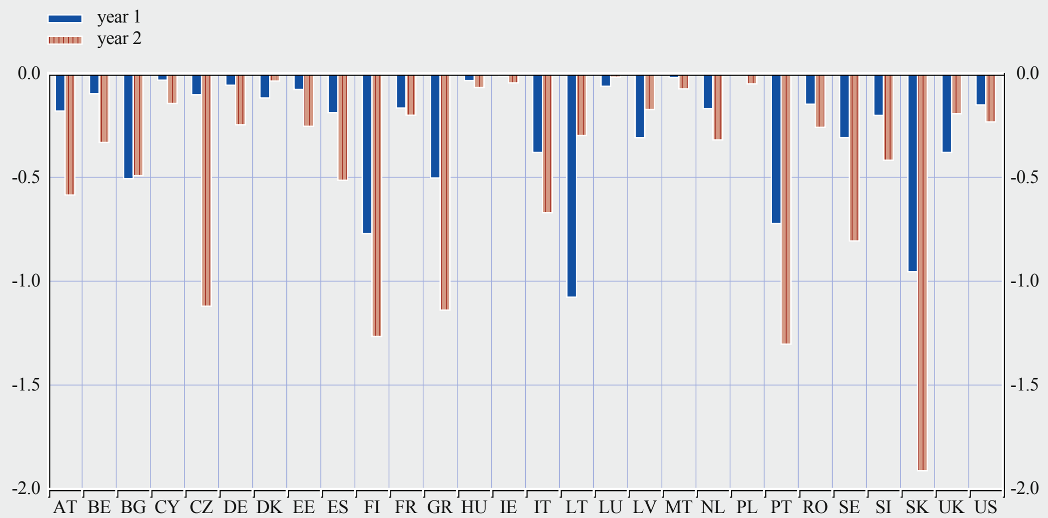


Source: ECB calculations.

found to be much stronger in Spain, Greece, Italy and Portugal. In other words, the scenario generation module is (and should be) able to reflect the fact that banks in different countries may be more or less exposed to, and hence will be affected differently by, the materialisation of a given systemic risk.

Chart 6 Cross-country scenarios for price inflation (two-year horizon)

(percentage deviation from baseline levels)



Source: ECB calculations.

Notably, the scenario generation process described above relates only to the adverse scenarios, and the output is usually expressed in terms of deviations from baseline levels (or growth rates). Baseline forecasts typically rely on those developed by the European Commission (EC) and the IMF, both published on a bi-annual basis, or on ECB staff macroeconomic projections.

2.2 TRANSLATION OF SCENARIOS VIA TOP-DOWN SATELLITE MODELS

In the following, the term 'top-down satellite model' is used to refer to an equation, or set of equations, that translates the macroeconomic scenario generated in the module described in Section 2.1 into an impact on the various forms of risks held by banks on their balance sheets (e.g. credit risk, interest rate risk, other market risks) and also on the banks' profitability, or loss-bearing capacity. This section describes the top-down satellite models developed at the ECB and employed for the translation of macroeconomic scenarios into banks' credit risk parameters (Section 2.2.1), interest rate risk components (Section 2.2.2) and, potentially, market risk parameters (Section 2.2.3).

Within the ECB framework, the top-down satellite modelling technique applied to credit risk, bank retail rates and market risk parameters is characterised by two key features (see Box 1 for a methodological description):

1. Autoregressive Distributed Lag (ADL) models, where the left-hand side variable is a function of its own lagged history as well as contemporaneous and lagged real economy and financial market indicators. Importantly, the estimated equations are not used to generate 'unconditional' forecasts of credit risk indicators, but instead are conditional on the assumed paths for the predictors based on the macro-financial scenario.[25]

2. To address model uncertainty, a Bayesian model averaging approach is chosen to develop the set of satellite equations. A Bayesian approach to modelling is particularly useful for modelling banks' risk parameters to account for the inherent model uncertainty related to the fact that for many risk parameter variables, the data quality is often imperfect and the historical time-series are typically rather short.

To combine individual models for loans to non-financial corporations and loans to households for consumption to a 'posterior model', i.e. a selection of the best performing models to be 'averaged', out-of-sample criteria have been used to evaluate the individual equations (see Box 1 for details).

On top of the in- or out-of-sample criteria used to assess the conditional predictive accuracy of the individual equations that form the model space, sign restrictions on long-run multipliers[26] of each model's predictor variables have been imposed to guarantee that a stress scenario results in a stressed response of credit risk measures.[27]

25 Alternative paths for the left-hand side variable projections, still conditional on a macro-financial scenario path, can be generated by using a pre-defined upper bound of the conditional forward distribution that is generated from the underlying ADL model equations.
26 Long-run multipliers represent the sum of the coefficients of time-contemporaneous and further lags of exogenous model variables.
27 Model equations, that do not meet at least one sign criterion imposed on its predictor variables, are excluded from the final set of models, i.e. they receive a 'zero weight' at the subsequent model averaging stage.

Box 1

TOP-DOWN SATELLITE MODEL DESIGN – A BAYESIAN MODEL APPROACH WITH A STRESS-TEST PERSPECTIVE[1]

This Box describes the general top-down satellite model design procedure applied in the ECB solvency analysis framework. It is widely applicable across the various forms of risks that banks face. Specifically, the satellite model design module is applied to credit risk, to interest rate risk and to other types of market risk (e.g. affecting the trading portfolio). Concretely, a satellite equation is used to translate an assumed scenario (baseline or adverse) into a path for the dependent variable that captures some risk pertaining to a bank's balance sheets.[2]

A Bayesian model averaging approach

To explicitly acknowledge the model uncertainty surrounding the projection of bank-related risk factors, a Bayesian model averaging approach is employed to structure a satellite equation for a dependent variable as a function of a set of predictor variables. This is a particularly useful approach for applications in a stress test context, since time series for dependent variables (e.g. loan loss rates, probabilities of default, etc.) tend to be short, thereby constraining the effective size of a single model equation. Specifically, a model pooling approach, with model weights implied by some Bayesian criterion, is useful as it allows for more predictor variables (ideally capturing all relevant ones) in explaining the dynamics of a dependent variable and ideally will result in projections that are more robust compared to those of a single equation.[3]

Autoregressive Distributed Lag (ADL) model

For defining the model space (the set of candidate equations), an Autoregressive Distributed Lag (ADL) model structure is chosen. For a single equation, the general format is therefore as follows:

$$Y_t = \alpha + {}_{P1} Y_{t\text{-}1} + \ldots + {}_{Pp} Y_{t\text{-}p} + \sum_{k=1}^{k_i} (\beta_0^k X_t^k + \ldots + \beta_{qk}^k X_{t\text{-}qk}^k) + \varepsilon_t$$

where Y is the dependent variable and X^k the independent variables from a set of *K* predictors. The ADL model structure is flexible in the sense that both contemporaneous and lagged dependencies with predictor variables are allowed. The lag structure of the model with regard to autoregressive lags (*p*) and further distributed lags of the exogenous model variables (k_1) is set by means of a specification search which considers all conceivable combinations of lag numbers up to a limit *G*. The specification that yields the optimal value of a criterion such as Akaike or Schwarz would be chosen.

For defining the model space for a dependent variable *Y*, all conceivable combinations of *K* predictor variables are evaluated. To keep the estimations tractable, the dimension (i.e. the

1 Prepared by Marco Gross.
2 An important aspect to be kept in mind is that a satellite model approach to balance sheet items as a function of macro and financial variables implies that bank balance sheet developments are not allowed to exert feedback effects to financial markets or the real economy. Different strategies are conceivable to account for endogenous feedback in either direction (see Section 2.5).
3 Whether the model pooling approach is in fact superior to the best performing single equation regression can be proved empirically using out-of-sample back-testing techniques.

number of predictor variables) of any single equation is limited to a pre-defined maximum L.[4] In this case, the total number of equations I forming the model space can be computed as follows:

$$I = \sum_{l=1}^{L} \frac{K!}{l!(K-l)!}$$

The following formula (from Bayes' rule) specifies how the individual posterior coefficient estimates from all single equations are combined to a posterior model for the dependent variable Y:

$$h(\beta|y) = \sum_{i=1}^{I} P(M_i|y) \frac{f(y|\beta)h(\beta|M_i)}{f(y|M_i)}$$

The equation shows that the posterior model probabilities $P(M_i|y)$ are used to compute a weighted average of the individual equations where $f(y|\beta)$ is the density function of the dependent variable, y, conditional on the predictor coefficient (β); $f(y|M_i)$ is the density function of y conditional on the model; and $h(\beta| M_i)$ is the density function of β conditional on the model. For further details as to the rationale and technical aspects behind the modelling averaging approach, and specifically the Bayesian averaging of classical estimates (BACE) as employed here for the purpose of structuring satellite equations, see Sala-i-Martin et al. (2004).[5] In line with the BACE approach, a minimum of prior assumptions are imposed on the parameters ("diffuse priors", implying use of the same priors for all predictors and no imposition of constraints on the distribution of their coefficients), which implies that the individual equations in the model space can be estimated by classical ordinary least squares.

Model evaluation approaches

A crucial question concerns how the posterior model probabilities (weights) $P(M_i|y)$ should be computed. Generally speaking, they are made proportional to a measure that evaluates the performance of any single equation. Two different approaches are conceivable:

The first method refers to in-sample measures of fit such as a Bayesian Information Criterion (BIC). Such a measure also addresses the trade-off between model size and fit (by penalising larger models). A second option is to refer explicitly to some measure of out-of-sample performance, to which the posterior model weights would be made proportional. This would necessitate an out-of-sample projection exercise using (a sufficiently long) realised history of predictor variables.

Out-of-sample measures to which model weights can be made proportional include point forecast (here, projection) accuracy measures such as Root Mean Square Errors (RMSE), or density forecast (here projection) accuracy measures such as Log Scores (LS) or Continuously Ranked Probability Scores (CRPS).[6] Directional accuracy measures, such as the proportion of correctly predicted changes over a given horizon or signal-to-noise ratios, can also be employed. Directional measures, however, tend to be 'not fine enough', at least if used as the only reference

4 Since not all 2^K variable combinations need to be considered, the model space defined in conjunction with a maximum size assumption can generally be estimated in its entirety, thereby obviating the use of stochastic search algorithms.
5 Hitherto the BACE methodology has mainly been applied in the economic growth literature.
6 Density accuracy measures can, moreover, be unweighted or weighted, the latter for the tails of the dependent variables' distribution to receive more weight (for example, the right tail when probabilities of default are considered as a dependent variable). The rationale for doing so is that one would aim to identify models (assign greater weight to models) that predict well in particular in the region of the distribution that we expect to reach under a hypothetical, adverse stress scenario.

to determining model weights, because they tend to be equal for at least a subset of models. A combination with other out-of-sample (point or density) criteria is therefore advisable.

MODEL OUTPUT

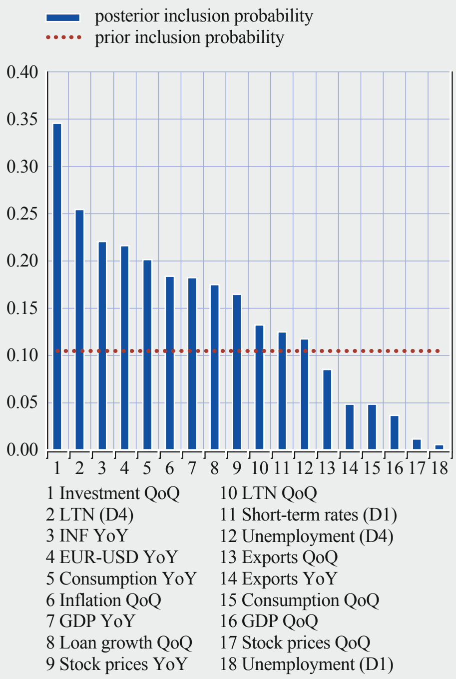
The output of the Bayesian model routine, while many different measures are available, can be cast in two forms in particular. First, *posterior coefficient means*, which for presentational reasons can be compressed into a long-run multiplier, can be presented. The long-run multiplier for a particular predictor can be computed as follows:

$$\sum_{l=0}^{\infty} \partial E\,(Y_{t+l}) \,/\, \partial X_t^k = (\beta_0^k + \ldots + \beta_q^k) \,/\, (1 - \rho_1 - \ldots - \rho_p) \equiv \Theta^k$$

The long-run multipliers can be *normalised* by multiplying the initial posterior coefficient estimates with the ratio of the standard deviations of the respective predictor and the dependent variable of the model. The normalisation has the advantage that resulting normalised long-run multipliers can be compared in magnitude to allow judging the relative importance

Chart A Posterior inclusion probabilities – Model for NPL

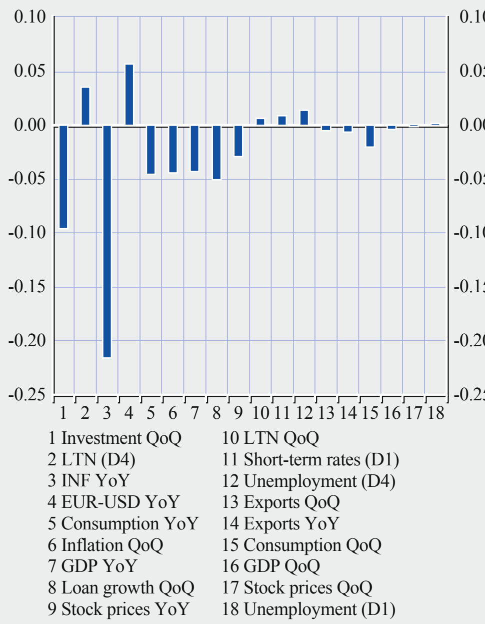
(percentage)



Source: ECB calculations.
Abbreviated variables: Long-term interest rates (LTN), price inflation (INF). Overall, 37 model variables were allowed to enter as potential predictors; the first 18 appear in the Chart. The maximum size of the model equations was constrained to four, with two additional lags of each being allowed at maximum. The total number of equations that the Bayesian model search therefore considered was equal 74,518.

Chart B Normalised long-run multipliers – Model for NPL

(multiple of a standard deviation of the NPL in quarterly log differences)



Source: ECB calculations.

(contributions) across predictors. Moreover, the sign of the long-run multiplier is of particular interest, as it shows the eventual impact on the dependent variable once the predictor is assumed to evolve along some baseline or adverse scenario path.

A second key measure is the *posterior inclusion probability* for single predictor variables, which is computed by summing the posterior model probabilities from the models that contain a particular predictor. Variables for which the posterior inclusion probability exceeds the prior inclusion probability[7] are said to be 'significant'.

To exemplify what the output of the model routine looks like, Charts A and B present posterior inclusion probabilities and normalised long-run multipliers, respectively. The underlying dependent variable was an aggregate non-performing loan variable (modelled in first differences of logarithmic levels) for a representative European banking system.

Chart A suggests that twelve variables are 'significant' according to the criterion that the posterior exceed the prior inclusion probability. Long-run multiplier estimates (Chart B) for investment, for instance, suggest that a one standard deviation decrease in investment would be associated with about one tenth of a standard deviation increase in NPL growth quarter on quarter. Most pronounced appears the role of price inflation (year on year), with the multiplier equalling about -0.2. All the predictors considered here have the sign that would imply stress, i.e. would let NPLs rise conditional upon an adverse scenario.

7 The *prior inclusion probability* reflects the likelihood that a variable is included in the model. Due to the use of "diffuse priors", this probability is the same across all variables. Technically, the prior inclusion probability is defined as the ratio of average model size to the number of predictor variables.

2.2.1 CREDIT RISK MODELS

For most banks, credit-related losses resulting from their borrowers' failure to meet contractual loan obligations are the major risk component with potential to substantially impair their assets and ultimately their capital adequacy. For this reason, from a macro stress testing perspective, the modelling and projection of credit risk is a key element in the overall analytical framework used for conducting a forward-looking solvency assessment.

The link between aggregate credit risk parameters and macroeconomic variables has been widely analysed. The earlier part of the literature explores the nature of the link between aggregate failure rates and different types of macroeconomic variables; see e.g. Altman (1983). In his seminal paper, Altman finds that general business cycle indicators, such as GDP growth, are negatively related to aggregate failure rates. However, many other types of macroeconomic variables, such as aggregate corporate birth rates (e.g. Hudson, 1986, 1989; Johnson and Parker, 1996), inflation (Wadhwani, 1986), exchange rates (Vlieghe, 2001), unemployment (Hudson, 1997), wage levels (Chen and Williams, 1999) and interest rates (Liu and Wilson, 2002) have been found to be related to probabilities of default.[28] The modelling of the relationship between LGD (or recovery rates) and macroeconomic variables only emerged recently, with the advent of the Basel Capital Accord. However, the focus of this research pertains to recoveries on corporate bonds rather than loans (for a review, see e.g. Altman, 2009). This is due to the fact that loans are private instruments and, therefore, few data are publicly available to researchers. Usually, recoveries on bank loans are larger

28 For two recent papers focused on modelling credit risk in the euro area, see Castrén et al. (2009, 2010). For a more encompassing survey of the literature on credit risk modelling, see for example Foglia (2008) and Saldiàs (2013).

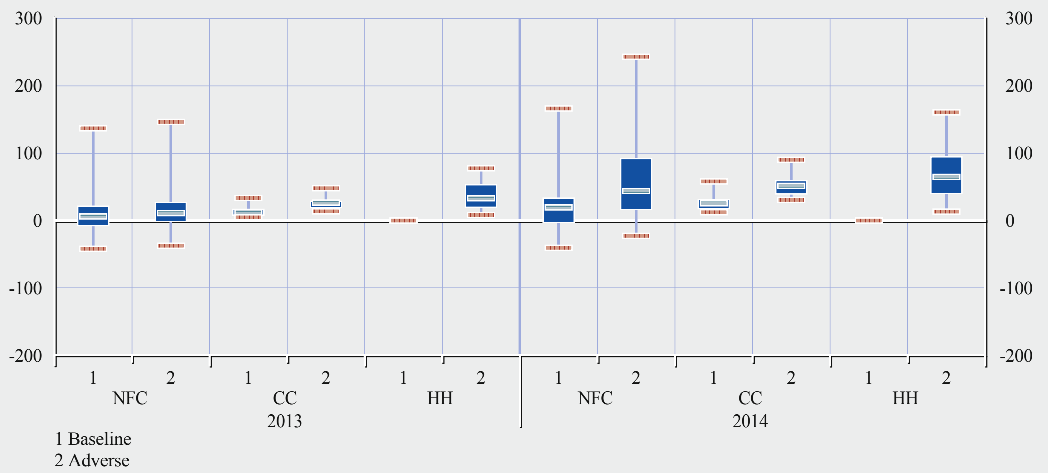
than those on corporate bonds. Schuermann (2004) finds that this difference may be attributed to the typically high seniority of loans with respect to bonds and the more active supervision of the financial health of loan debtors pursued by banks.

The most prominent economic indicators for the analysis of credit risk include Probabilities of Default (PDs), Loss Given Default (LGD) and Loss Rates (LRs), with the LR being the product of PD and LGD. Additional 'balance-sheet'-type indicators that can be used in parallel to assess credit risk are the amounts of Non-Performing Loans (NPLs) and the stock of Loan Loss Reserves (LLRs). NPLs can be expressed as ratios to gross loans. LLRs can be expressed relative to the outstanding amounts of NPL, a ratio which is referred to as the "coverage ratio". Moreover, Monetary Financial Institutions (MFI) statistics on country-specific banking sector Write-off Rates (WRO) can serve as an additional measure of credit risk, although this measure is likely to reflect a rather delayed credit risk response, as write-offs are the final step in banks' process of recognising credit losses. Finally, default rates (e.g. the number of defaulting loans to total outstanding loans) are another source of information that can be used as a credit risk indicator. Arguably, the various measures of credit risk have somewhat overlapping definitions but can be considered to differ in terms of their time perspective with PDs, measuring the probability of borrower default x-days ahead, being the most forward-looking metric and WROs, reflecting the point in time when non-performing loans are ultimately written off, being the least forward-looking metric, respectively.

Depending on the context, ECB staff satellite models use one of the sources mentioned above as a dependent variable. For country-specific analysis, NPL information is usually considered, while WRO – being the only data source for which harmonised definitions and data exist across all euro area countries – are used in the context of cross-country analysis. Apart from its wider geographical scope, a further advantage of the WRO series is the fact that they include a sectoral breakdown distinguishing between loans to non-financial corporations, household loans for house purchase, and household loans for consumption. Satellite models have been developed for all these three categories.

Chart 7 Write-off-rate scenario responses

(percentage change from end-sample levels; minimum, maximum, median and interquartile ranges of country-specific responses)



Source: ECB calculations.
Notes: "NFC" refers to non-financial corporations, "CC" refers to consumer credit and "HH" refers to mortgage credit.

In parallel to using this model framework for obtaining satellite projections for WRO paths at the euro area level, the models are used to compute projections at the country level, by feeding country-specific assumptions for macro and financial variables through the model. As an illustration, Chart 7 presents the responses of WROs conditional on an illustrative country-specific adverse macroeconomic scenario, with the responses expressed in cumulative percentage changes from end-sample levels. As should be expected, loan losses tend to be larger under the adverse scenario than under the baseline across all three portfolio segments.

2.2.2 RETAIL INTEREST RATE MODELS

For modelling retail interest rates, the same ADL model approach and Bayesian model averaging technique as used for modelling credit risk is employed.[29] Interest rate data for loans and deposits are taken from the ECB's MFI Interest Rate (MIR) statistics. The database contains country and euro area aggregate series of retail interest rates applied by monetary and financial institutions to deposits and loans vis-à-vis households and non-financial corporations.

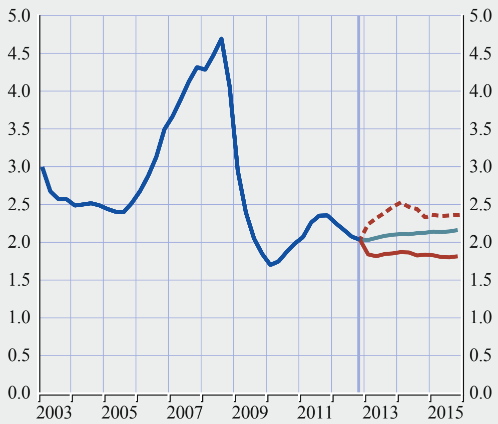
The data encompass retail rates on new business as well as on outstanding amounts. For new business rates, ten broad categories are employed:[30] five types of lending rates and five deposit rates. Specifically, the deposit category includes rates on sight and term accounts for both households and corporate clients and savings deposits ('redeemable at notice') taken from households. The lending rate category includes interest rates on loans to households for consumption, loans to households for house purchase, and loans to the corporate sector, in addition to overdraft loans to households and to non-financial corporations. For interest rates on outstanding amounts, the aggregate interest rates on loans to households for house purchase and for consumption are used, as well as rates on loans to non-financial corporations. On the deposit side, a distinction is made between interest rates on deposits from households and from non-financial corporations.

As with the modelling approach used for credit risk and for modelling retail interest rates, the list of predictor variables used to establish the model space is comprehensive, containing a wide range of financial and real economic variables.[31]

Charts 8 and 9 illustrate how rates for outstanding deposits and loans from and to the euro area corporate sector would evolve conditional upon the assumed baseline and adverse scenario. For the adverse scenario, two variants are presented.

Chart 8 Projected corporate sector-term deposit rates

(percentage; petrol blue line is baseline; dashed reddish brown line includes shock to market rate; solid reddish brown includes shock to real economy only)



Source: ECB calculations.

29 The details of the retail interest rate models are described in Gross and Kok (2013b).

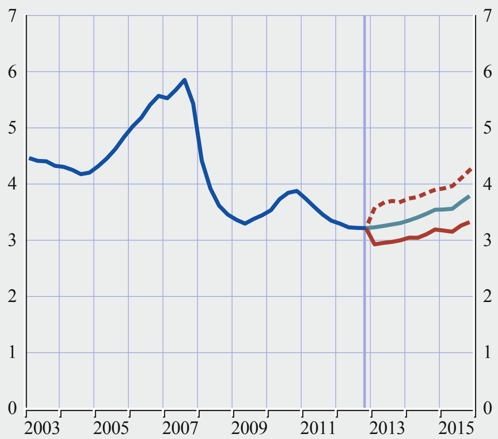
30 In practice, more granular product breakdowns are available, but to keep things tractable some aggregation (e.g. across maturities and initial rate fixation) has been done prior to estimation.

31 The literature on bank retail interest rate pass-through typically finds that banks tend to only sluggishly adjust their retail rates to changes in official rates, as due to asymmetric information banks are often able to exploit a certain degree of market power when setting their retail prices; for a survey of the literature see the article entitled "Recent developments in the retail interest rate pass-through of the euro area" in the August 2009 ECB *Monthly Bulletin* and references therein. See also the article entitled "Assessing the retail bank interest rate pass-through across the euro area at times of financial fragmentation" in the August 2013 ECB *Monthly Bulletin*.

The first (reddish solid line) includes real economic shocks, whereas the second (reddish dashed line) involves an additional (permanent) positive shock to short-term money market interest rates. The resulting projections suggest that, as expected, there is a considerable role for the pass-through from money market interest rates to retail deposit and loan rates. Under the adverse scenario including the short-term rate shock, both deposit and loan rates would be projected to increase relative to the baseline, causing both interest expenses for deposits and interest income on loans to increase.

Chart 9 Projected corporate sector loan rates

(percentage; petrol blue line is baseline; dashed reddish brown line includes shock to market rate; solid reddish brown includes shock to real economy only)



Source: ECB calculations.

When excluding the shock to money market rates, both deposit and loan rates would be projected to fall relative to the baseline scenario. As regards the underlying factors that determine these projections, apart from the positive multiplier capturing the pass-through from money markets, it can be noted that long-run multipliers have positive signs on real activity measures such as real GDP and negative signs on variables such as the unemployment rate. This suggests that, on average, demand-side factors have tended to dominate supply-side factors linked to borrower creditworthiness.[32]

2.2.3 MARKET RISK MODELS

The stress test of the trading book usually requires banks to project gains and losses on the trading book positions resulting from a broad-based financial market downturn that affects a broad set of market risk parameters, such as interest rates, exchange rates, equity and commodity prices, dividend yields and volatilities. To ensure sufficient severity, such an adverse scenario is usually assumed to be an instantaneous, one-off shock affecting the trading book without any room for management action which would reduce the institution's trading exposures, as markets would be considered illiquid. Market risk parameter stress can either be set ad-hoc, on the basis of historical information, or depend on the scenario assumptions for the evolution of some macro-financial variables – such as short- and long-term interest rates, exchange rates, and stock prices.

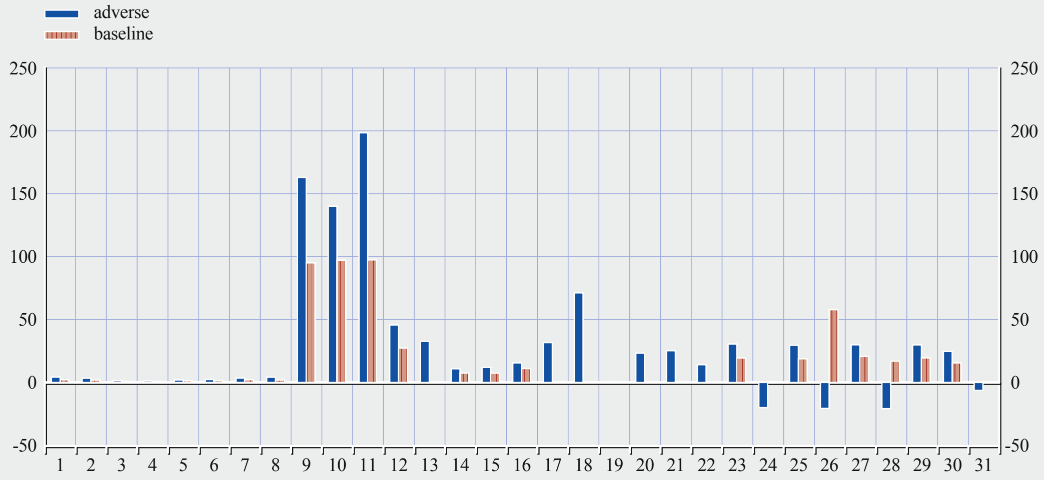
The ECB stress testing framework is currently not well suited to calculating losses for banks' trading books, since granular trading book portfolio information is generally not available. However, the ECB has developed a modelling methodology that can be employed to derive market risk stress parameters.[33] Similar to the modelling of credit and interest rate risks, the market risk parameter model specification is based on a search algorithm using ADL regressions and employing standard information criteria combined with sign restrictions on long-run multipliers set up to ensure that the response to shocks is broadly in line with economic theory.

32 A priori, the impact of economic activity on banks' lending rates is ambiguous. While an economic contraction would be expected to reduce loan demand, thereby creating downward pressure on lending rates, it would also tend to increase risk premia, hence putting upward pressure on lending rates.

33 The ECB market risk parameter modelling framework was used, for example, in the context of the 2011 EBA EU-wide stress testing exercise.

Chart 10 Market risk parameter projections

(basis point change from starting level unless otherwise indicated)



1 CBS BBB 5-7 years
2 CBS BBB 3-5 years
3 CBS AAA 5-7 years
4 CBS AAA 3-5 years
5 CBS AA 5-7 years
6 CBS AA 3-5 years
7 CBS A 5-7 years
8 CBS A 3-5 years
9 Itraxx CDX Lev
10 Itraxx CDX IG
11 Itraxx CDX HY
12 oil price volatility
13 volatility 3-month EURIBOR (percentage from baseline)
14 volatility EUR/USD
15 volatility GBP/USD
16 volatility JPY/USD
17 volatility 3-month rate US (percentage from baseline)
18 volatility 3-month rate Japan (percentage from baseline)
19 3-month money market rate Japan
20 bond market vola9lity Japan (percentage from baseline)
21 bond market volatility US (percentage from baseline)
22 market volatility euro area (percentage from baseline)
23 Gold price volatility
24 Gold price (percentage from baseline)
25 MSCI volatility
26 MSCI
27 Nikkei volatility
28 Nikkei
29 Eurostoxx50 volatility
30 S&P 500 volatility
31 S&P 500 (bps from baseline)

Source: ECB calculations.

This modelling framework covers, in total, over 40 market risk parameters across over 10 jurisdictions: stock prices, credit spreads, swap rates, volatility parameters and macro-financial variables. The links to the macro-financial scenario are constructed using the financial variables which are commonly directly stressed in the adverse macro scenarios (for example, stock prices in the US and the euro area, and money market interest rates). These variables are in turn used as shock origins for the remaining market risk parameters to be estimated. Chart 10 illustrates a translation of the baseline and adverse macroeconomic scenarios into various market risk parameters using the modelling framework. Especially, under the adverse scenario, notable increases of CDS spreads and various volatility measures are observed, while stock market indices tend to decline. Market risk shocks are typically assumed to occur instantaneously and then either gradually fade out over the horizon of the stress test or to remain constant throughout.

Position data is only available in the public domain for a limited class of assets sensitive to market risk, notably sovereign and some corporate credit exposures held in the trading book. In the stress testing framework, those exposures are modelled separately from banking book exposures.[34] The adverse movements in the credit spreads on those exposures are usually explicit in the scenario and are used to estimate the resulting price movements. To this end, a representative sample of underlying sovereign or corporate bonds is priced twice: (i) on the cut-off date of the scenario

34 For banking book exposures (not related to corporate and retail customer loans) provisioning is generally based on rating-implied PDs similar to the EBA EU-wide stress test exercise; see EBA "2011 EU-wide Stress Test: Methodological Note – Additional Guidance", 9 June 2011.

and (ii) following the shock, which is applied immediately to avoid the mitigating impact of time decay.[35] The price impact estimate is consistent with the relevant market practices and conventions.

2.3 SOLVENCY CALCULATIONS

This section describes the third pillar of the framework; namely, the various steps needed to calculate individual bank solvency positions once the scenarios have been fed through the satellite models. The calculations described in this section are carried out at the level of individual banks and require granular information about the balance sheets and income statements of the banks included in the analysis (Box 2 provides a description of data requirements related to top-down forward-looking solvency analysis).

35 For a bond trading below par, the passage of time will result in price gains even if the actual credit spread remains constant. As the horizon of the scenarios considered in stress tests is usually between two and three years, this effect becomes material and substantially mitigates the adverse impact of credit spread shocks.

Box 2

DATA REQUIRED FOR CONDUCTING TOP-DOWN SOLVENCY ANALYSIS[1]

I. Data needs – general considerations

Stress test data requirements are generally very demanding. In addition to individual bank data over time and across a number of dimensions, the country-specific macro-financial data that form the baseline and adverse scenarios used in the stress test are an integrant part of the exercise. This box focuses only on the former category of data needs in reviewing the main bank-specific data needs.

Banking sector stress tests are typically conducted on individual bank data irrespective of the test modality. Stress tests can be conducted by individual banks in a bottom-up fashion (in cooperation with the respective supervisory authorities, using individual or common scenarios for all institutions) or they can be conducted in a centralised manner in a top-down fashion, without the direct involvement of individual banks, typically using a common scenario for all institutions. In the latter case, harmonised bank-level data is particularly important for comparability and the overall quality of results.

It goes without saying that data quality is a key determinant of the reliability of any stress test results. The quality and granularity of the data used in stress test exercises crucially depends on data availability, usually banks' financial reporting, pillar III disclosures and, ideally, proprietary supervisory information. In the case of centralised exercises run with supervisory data, the granularity of the data needs could depend on the ultimate purpose of the exercise. This can range from an assessment of overall soundness of individual banks or the banking sector to the estimation of provisioning or capital targets to back supervisory actions and requests imposed on banks, where rigour in the data input is crucial.

1 Prepared by Inês Cabral and Markus Kolb.

II. Data needs – key variables

The bulk of variables used in stress testing exercises are bank-specific as reported in the bank balance sheet, asset quality and profit and loss data. Individual bank level data are typically employed to evaluate the output from the credit risk, market risk and profitability models in terms of impact on the banks' profit and loss accounts and on their balance sheets (as described in Section 2.3). Furthermore, data input is also needed to model feedback effects, going beyond the direct impact of shocks on an individual bank. In this context, the availability of sufficiently granular data particularly relate to interbank exposures to model contagion in the banking sector.

While stress tests are typically conducted on banks' consolidated data, the specific purpose of the test (e.g. assess the solvency of foreign subsidiaries) may require the use of sub-consolidated levels of a banking group's data. Key to the quality of the stress test results are not so much the core balance sheet and profit and loss variables, as published in banks' financial statements, but their breakdowns across a number of dimensions.

On the asset side, critical to the assessment of loan losses is the simultaneous breakdown of loans and receivables by portfolio (e.g. large corporates, small and medium-sized enterprises (SMEs), commercial real estate, housing, consumer retail, sovereigns and financial institutions) and geographical dimensions (by individual country), where applicable. Moreover, information on PDs and LGDs (or related measures of credit risk, such as NPLs, loan-loss provisions or write-off rates), provided by the same breakdowns is essential for conducting top-down stress tests. The information on risk-weighted assets for these credit exposures is also needed for a consistent analysis of credit risk. Beyond the asset quality information for the relevant quarter, there is the need for sufficiently long historical time series to allow for the projection of asset quality indicators for the test horizon.

Profitability modelling requires detailed breakdowns of income and expense items along its sub-components, broken down across countries in the case of cross-border banks. Information on the type of interest rate contract, average maturity and interest rate on key assets (loans and receivables) and liabilities (categories of deposits and other main financial liabilities) are also important data inputs to assess effects on profitability and overall balance-sheet adjustment to shocks.

Concerning market risk data, trading book data – as well as by accounting portfolio (available-for-sale, held-to-maturity positions) and by type of security (bonds, equities, structured) – are essential to understand the sensitivity of banks' balance sheets to market risk.[2] Further information about the nature of the underlying assets (counterparty type, instrument type, underlying risk, maturity, etc.) as well as hedging positions is crucial to be able to precisely assess and stress banks' market risk.

Where data are not available, country-specific parameters or assumptions on the basis of other banks with similar size and business model are generally used, implying caveats and the need to exercise appropriate caution in the interpretation of results.

2 In particular, data on sovereign debt holdings in each accounting portfolio broken down by country and maturity are essential information needs for stress testing in the present context, in which sovereign debt strains remain elevated.

III. Data sources

Bank solvency analysis using stress testing tools, conducted by the ECB and regularly published in the *Financial Stability Review*, is fully based on publicly available information. The balance sheet and profit and loss data are taken from banks' published financial reports, but also take into account supervisory information (in particular, regarding the granular geographical breakdowns of exposures at default) disclosed in the context of the EBA 2011 EU-wide stress test and the EBA 2012 EU Capital Exercise. The exercises are typically run with consolidated data at the banking group level.

Regarding the ECB analytical support provided in the context of EU/IMF programmes where stress testing exercises are conducted, or in the support provided to peer review processes of EU-wide stress testing exercises under the aegis of the EBA, supervisory data is generally used. This is essential to ensure the appropriate quality and an accurate starting point upon which projections are based so as to guarantee comparability of results.

2.3.1 STATIC VERSUS DYNAMIC BANK BALANCE SHEETS

Macro stress testing exercises can be based on either static or dynamic balance sheet assumptions. The latter is clearly more realistic (as banks' balance sheets are never completely static), whereas the static assumption can be more adequate for purposes such as bottom-up stress tests carried out at the bank level under supervisory guidance. In the second case, it can be difficult for the supervisor to attest whether or not banks would exploit any imposed dynamism to mitigate the stress on their own results. However, from a top-down perspective where the stress test calculations are carried out without directly involving the banks, it is comparatively easier to incorporate some degree of dynamic behaviour. For these reasons, the balance sheet modelling in the ECB top-down stress test is based on a *dynamic balance sheet* tool so that it can apply either exogenously given or endogenously optimised paths for key balance sheet items. Of course, the tool also makes it possible to assume constant balance sheets.

Dynamic balance sheet with an exogenous path for key balance sheet items

The exogenously given dynamic balance sheet module incorporates country-specific regulatory and macro-financial developments or restrictions faced by individual banks over a given stress test horizon. With this approach, the stress test analyst can apply relatively realistic scenarios of changes in bank balance sheet structures reflecting anticipated changes in market demand for bank products, funding conditions and bank reactions to the economic cycle. The approach also allows for a bank-specific treatment in cases where authorities have set a mandatory restructuring plan, for example in response to state-aid rulings, or in cases where acquisitions or divestments have already been completed but are not yet reflected in the initial balance sheet.[36]

The starting point for the projection of the balance sheet evolution is the level of balance sheet items at the stress test cut-off date. Then, exogenously given paths for key balance sheet items over a stress testing horizon are applied. These are based on a set of assumptions and projections from satellite models and/or expert judgement. For certain items, caps or floors are applied so that the change of the balance sheet composition remains consistent with the macroeconomic scenario or anticipated market conditions. Notably, each bank in the system can be modelled individually using

36 For a more detailed analysis of EU bank deleveraging, see also ECB *Financial Stability Review*, June 2012, Special Feature A, entitled "EU bank deleveraging – driving forces and strategies", and ECB *Financial Stability Review*, May 2013, Box 5, entitled "Deleveraging by EU banks".

bank-specific starting points for balance sheet items. The key balance sheet items that are usually projected comprise:

i. Cash and balances with central banks;

ii. Securities holdings – further broken down by type of instruments and sector for debt securities (e.g. a special focus on government bonds and T-bills);

iii. Loans and receivables to banks, corporates, commercial real estate, mortgages, consumer credit, government;

iv. Deposits – split by sector and maturity;

v. Debt securities issued – split by maturity;

vi. Central bank funding – separately for main refinancing operations (MRO) and emergency liquidity assistance (ELA).

The tool requires a residual (i.e. balancing) category either on the (i) asset side (e.g. credit) or on the (ii) liability side (e.g. funding) when equating the left- and right-hand sides of the balance sheet. When funding is the residual category, any funding needs that cannot be covered in the market (i.e.interbank market, debt issuance, deposits) are typically assumed to be satisfied with an increased reliance on central bank funding, collateral permitting. It is worth noting that the dynamic balance sheet tool can take into account the impact of any expected future capital injection (in the form of cash or marketable securities) on banks' funding volume and structure. This is particularly relevant for top-down stress test exercises in EU/IMF programme countries, where funding strains are usually high and any expected capital injection has a significant impact on the availability of funding and the ability of banks to provide credit to the economy.

The dynamic balance sheet tool obviously allows for a *static balance sheet* assumption whereby all balance sheet items are retained at the reference levels over a stress test horizon. Under this assumption, banks do not strategically react to shocks by taking management actions or adjusting their business strategy.

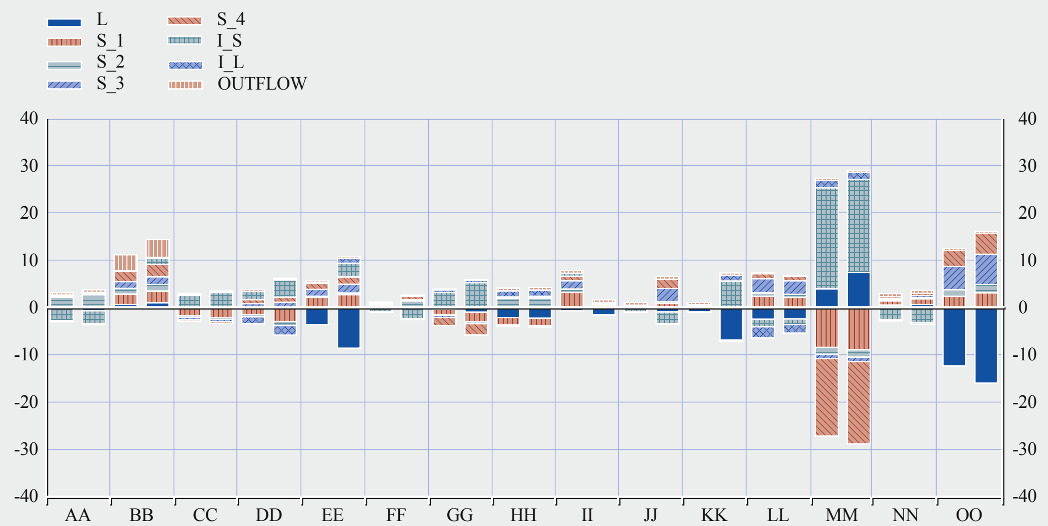
Dynamic balance sheet with an endogenous path for key balance sheet items

The dynamic balance sheet approach may reflect either changing customer demand for banks' products, dynamic funding conditions or behavioural aspects of banks' activities responding to the business cycle. However, as Borio et al. (2012) notice, "some [stress test] models allow for the possibility that banks adjust their balance sheets in response to the shocks, although so far only through mechanical rules of thumb". Usually, the response implies some form of 'fire sale' of assets following a pre-defined pecking order (Aikman et al., 2009). Drehmann et al. (2010) consider banks as passive investors whose assets evolve according to estimated default probabilities (PD) and losses given default (LGD). Notably, they also model the dynamics of banks' liabilities. Alessandri et al. (2009) describe the "rule of thumb" embedded into the stress testing model of the Bank of England (the so-called RAMSI model), which allows for changes in the asset composition when banks make profits. Moreover, the model assumes that banks target a leverage ratio and try to maintain the product structure of their assets.

The ECB forward-looking solvency framework likewise embeds a dynamic balance sheet module with an endogenous path for key balance sheet items based on banks' optimising behaviour. It is assumed that banks optimally restructure their assets following a risk-adjusted return maximisation programme. This risk-return optimisation mechanism is borrowed from the classical portfolio theory and adjusted in order to account for specific banking features, in particular capital and liquidity constraints. Specifically, banks are assumed to maximise their return on equity, adjusted by the covariance of risks in their balance sheets within one period (one year). The return encompasses the interest income and expenses broken down by broad product[37] and maturity categories. The net income flow is modelled as a sum of reference interest rates, to which a given balance sheet category is likely to be indexed, and the premium related to market risk, counterparty risk and credit risk.[38] Moreover, it takes into account the cost of capital calculated using a Capital Asset Pricing Model (CAPM) approach.

The application of the module in the stress testing context is straightforward. A stress testing macroeconomic scenario usually impacts risk parameters, such as interest rates, loan default probabilities and credit risk spreads (sovereign and individual bank), and induces banks to re-optimise their portfolio structure. Charts 11 and 12 illustrate the application of the tool to analyse reactions of banks in a sample of European banks to stylised baseline and adverse shocks projected for two periods (years) ahead. For illustrative purposes, results are here presented at the level of aggregate national banking sectors. For each country, labelled in the charts by a pair of letters (e.g. AA), the two stacked bars represent percentage changes of some aggregate asset categories after the first and second year of projection (comparing to the structure observed at the outset of the

Chart 11 Changes of asset structures under the baseline (country aggregate)



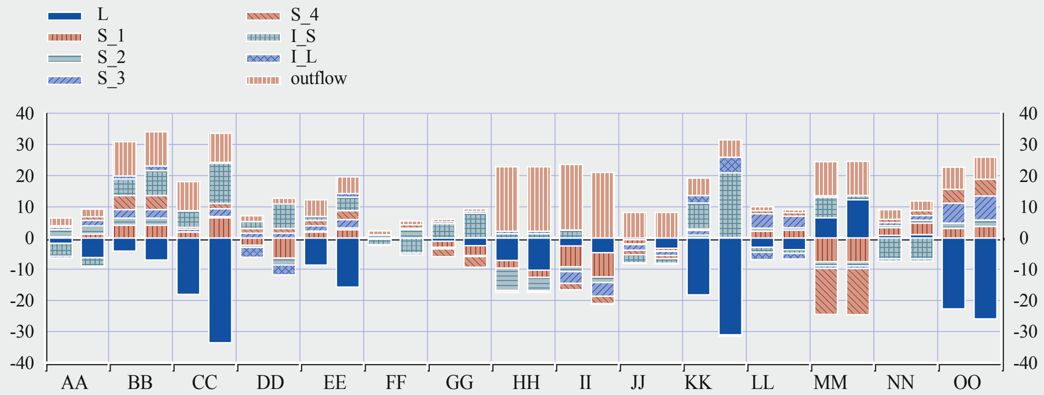
Sources: ECB and ECB calculations.
Notes: L – loans; S_n – securities in one of the four maturity buckets; I_S and I_L – short- and long-term interbank assets; OUTFLOW – reduction of assets driven by outflow of the funding sources.

37 The stylised balance sheet structure is assumed to be composed of loans to customers, debt securities and interbank placements on the asset side, and retail and corporate deposits, wholesale funding, own debt issued and capital (equity)

38 Details of the approach, which can technically be referred to as constrained linear-quadratic programing, and some sensitivity analysis of the resulting tool are presented in Hałaj (2013a).

Chart 12 Changes of asset structures under the adverse scenario (country aggregate)

(percentages; country aggregate)



Sources: ECB and ECB calculations.
Note: L – loans; S_n – securities in one of the four maturity buckets; I_S and I_L – short- and long-term interbank assets; OUTFLOW – reduction of assets driven by outflow of the funding sources.

horizon). The results of the stylised example confirm the strong heterogeneity of domestic banking systems in adapting to the market conditions. For example, one important implication of the model has to do with the reduction of lending following shocks to the macro-financial environment. The deleveraging of loan portfolios is mostly seen in banks from countries BB, CC, EE, JJ, KK, OO and LL. It will usually be the case that the magnitude of deleveraging is generally stronger under the adverse scenario (compare Charts 11 and 12).

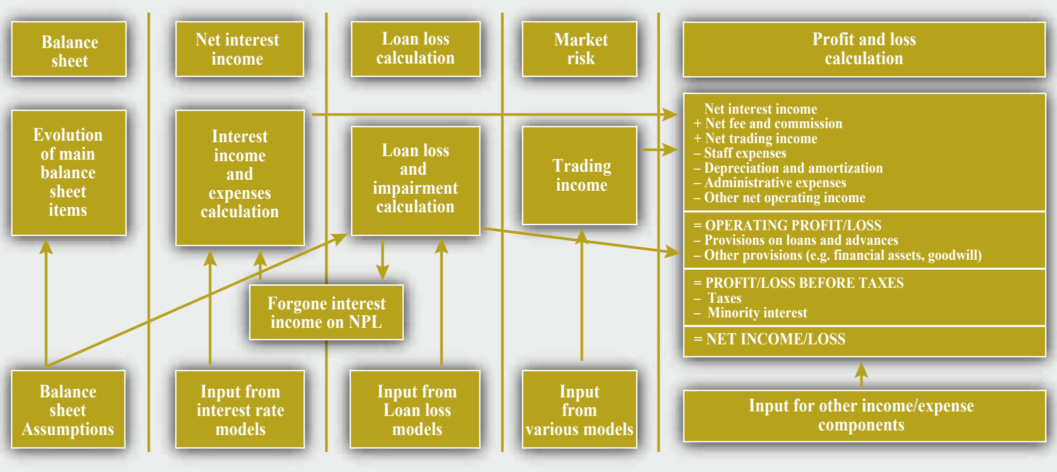
There are important caveats to the approach related to necessary simplifications of banks' behaviour and data limitations. First, the decision-making process is very simplified. Banks' asset and liability management systems are extremely complex decision support tools in which expert judgment plays a crucial role. Second, it is a one period model neglecting intertemporal effects.[39] Third, the liability structure is currently not included in the optimisation programme. In reality, banks can raise capital or apply an active pricing policy in order to attract or disencourage various groups of customers. Fourth, there is a significant estimation risk related to return and risk parameters, and correlations between them. These caveats notwithstanding, the tool is capable of projecting balance sheet dynamics in an endogenous manner consistent with the stress testing scenario. It can, therefore, provide a useful complementary assessment to the otherwise static or more judgemental exogenously given dynamic balance sheet tool.

2.3.2 PROFIT AND LOSS CALCULATIONS

In the profit and loss calculation, the assumptions and projections from the satellite modules are translated into revenues, expenses, losses and provisions. The approach can be divided into four modules: the net interest income calculation, the loan losses and impairment calculation, the market risk calculation and the final profit and loss calculation in accordance with the assumptions for other income components (see Chart 13).

39 However, it is implemented in such a way that the end of period structure is the starting balance sheet structure at the next consecutive period.

Chart 13 Schematic overview of the profit and loss calculation



Source:

In the net interest income module, interest income and expenses are calculated separately. The main input for the net interest income calculation is the evolution of the relevant balance sheet items (such as loans, deposits and wholesale funding) and the retail interest rate projections derived from the satellite modules described in Section 2.2.2. The country-specific projections and assumptions are translated for each year over the stress test horizon via annual changes or factors into balance sheet components of the participating institutions. This computation is done on the basis of a granular balance sheet breakdown by instrument, geography, maturity and counterpart sector, and it also considers bank-specific characteristics such as residual maturities and refinancing needs. Furthermore, foregone interest income on non-performing loans derived under the loan loss and impairment module needs to be taken into account when calculating the net interest income. The outcome of these calculations is a projected path for interest income and expenses for each participating institution over the stress test horizon.[40]

The second module, the loan loss and impairment calculation, combines the output from the balance sheet assumptions and the projection of asset quality indicators from the loan loss models to address the impact of credit risk. The module combines conditional projections of country-level credit risk with bank-specific balance sheet evolutions. The projected changes of the write-off rates at the country level described in Section 2.2.1 are then applied to bank-specific loss rates to calculate the expected losses. Considering existing asset protection schemes, the evolution of the exposure and LGDs, these results are subsequently translated into impairments over the stress test horizon. The impact of foregone interest income from non-performing/defaulting loans is subsequently calculated and subtracted from interest income.

The market risk module attempts to capture any profit and loss impact from the investment portfolio of the participating institutions. It applies the shocks (e.g. haircuts on the valuation of securities held on the trading book) derived from the market risk parameter model output to specific portfolios at a given point in time or over the stress test horizon.

40 The net interest income module mainly captures changes in interest income and expenses related to banks' retail customer business and their wholesale funding costs. Other interest-related income and expenses are assumed constant. In addition, no assumptions are made regarding changes in interest rate hedging over the forecast horizon.

In the final module, net interest income, loan loss impairments and the market risk impact for each of the participating institutions are merged with other income components. The profit and loss impact of these other components is derived from the output of a judgemental approach[41] in accordance with system-wide or bank-specific assumptions, such as minimum contribution to minority interests or constant tax rates. Chart 13 displays a schematic overview of the calculation. This approach allows a comparison of the evolution for each component and the overall profitability of the participating institutions.

2.3.3 RISK-WEIGHTED ASSET CALCULATIONS

The calculation of risk-weighted assets (RWA) complements the projected profits or losses of an institution with a conditional forecast of the future capital requirement at the end of the scenario horizon.[42]

The change of average risk weights for the loan portfolios is estimated on the basis of projected credit loss rates, using the Advanced Internal Rating-Based (IRB) formula of Basel II.[43] The calculations are made at the portfolio level, for three regulatory portfolios: corporate, residential mortgage and retail loans. For example, the Basel II formulae imply that risk-weighted assets equal K*12.5*EAD,[44] where, in the case of corporate exposures for example,[45]

$$K = \left[LGD * N \left(\sqrt{\frac{1}{1-R}} * G(PD) + \sqrt{\frac{R}{1-R}} * G(0.999) \right) - (LGD * PD) \right] * \frac{1 + (m - 2.5)\, b}{1 - 1.5b}$$

and where *N(x)* denotes the cumulative distribution function, *G(z)* denotes the inverse of the cumulative distribution function, *R* denotes the correlation (also a function of the PD), *M* is effective maturity and *b* denotes the maturity adjustment (as well a function of the PD).

By assumption, the LGD is held constant and the adjustment of the risk weights takes place solely through changes in PDs.[46] Moreover, the exposure at default is adjusted to reflect the institution-specific credit growth or credit contraction under the scenario. Finally, the fourth parameter of the A-IRB formula – maturity – is assumed to be constant and in line with the Foundation IRB approach.

Risk weights on assets, which are subject to capital measurement under the Standardised Approach of Basel II, are assumed constant. In practice, the risk weights on those assets do not depend on the actual PD, but only on external ratings; these, however, are available for only a small subset of exposures. In turn, the relationship between the risk weight and the LGD is non-linear, because of

41 The judgemental approach is typically based on past years' performance of other income or expense components, e.g. fee and commission income/expenses, staff expense or depreciation and amortisation. The covered time horizon depends mostly on the selected scenario and the availability of historical data. In order for a path to be conservative enough, a historic reference period over which an average is computed would be set to comprise a past recession period, e.g. covering the years 2007-2009.

42 The RWA concept was conceived by the Basel regulatory standards that govern minimum capital requirements in the EU and elsewhere. Under the Basel II (and Basel III) standards, banks are allowed to use their own internal credit risk models (if these have been approved by their supervisor) to calculate the denominator of their solvency ratio (i.e. the RWA) by weighing the assets according to their riskiness. This is the so-called "internal rating-based approach", which consists of either an "advanced" or "foundation" approach depending on the number of input parameters the banks are authorised to supply using their own models. Other banks whose internal models may not be sufficiently sophisticated apply the "standardised approach", in which risk parameters are pre-defined and fixed.

43 Bank-level information about the (partial) use of standardised methods has also been incorporated.

44 "EAD" refers to exposure at default.

45 See BCBS (2005), para. 272. Similar, though slightly different, RWA formulae are applied for the mortgage and retail customer portfolios.

46 Alternatively, the loss rates can be decomposed into PD and LGD, where a quadratic relationship between the changes in PD and LGD is assumed, so as to account for the stickiness of LGD. The corresponding set of two quadratic equations is solved under the condition that PD and LGD are both required not to decrease under stress.

the preferential treatment applied to some exposures secured by real estate and cannot be robustly estimated without recourse to micro data.

Risk-weighted assets relating to market and counterparty risk are scaled up by a fixed factor, in line with the minimum requirements set in the methodology of the 2011 EBA EU-wide stress testing exercise. The capital charges for operational and other risks are not stressed.

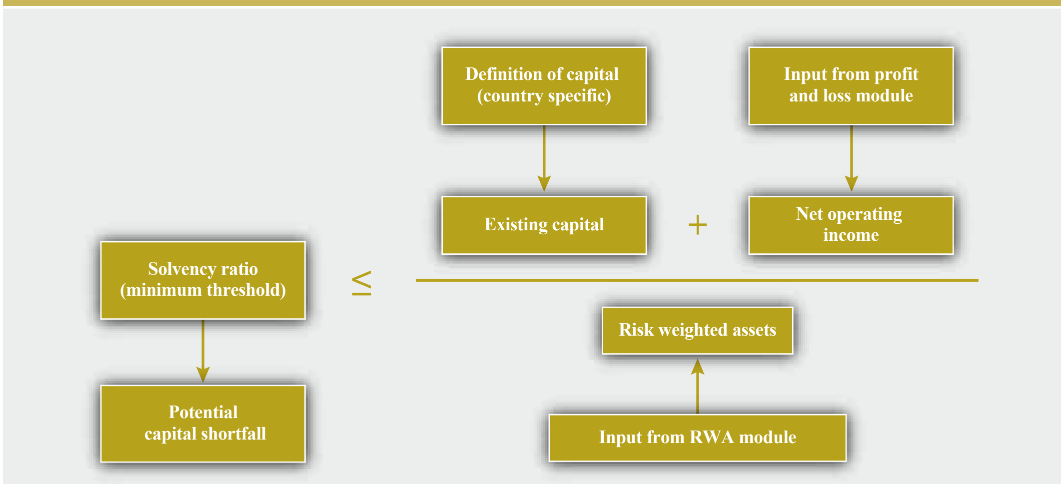
2.3.4 SOLVENCY CALCULATIONS USING THE BALANCE SHEET TOOL

This section describes how the outputs from the above-mentioned modules are merged and how the solvency positions of the participating institutions are calculated via the balance sheet tool.

The solvency calculation, the main objective of the stress test, comprises the definition and calculation method of capital, which includes net income and the output from the RWA tool. The end-horizon solvency ratio is calculated as the sum of the existing capital stock and earnings accumulated over the stress test period in relation to the end-horizon risk-weighted assets (see Chart 14).

The composition of capital applied in most of the exercises refers to the standard capital definition set by either the Basel Committee on Banking Supervision or the European Banking Authority, along with information on regulatory changes over the stress test horizon. Country-specific capital definitions or capital add-ons can complement the standard approach. Over the stress test horizon, the output from the profit and loss module and the risk-weighted asset module triggers changes in various capital ratios, such as the total capital ratio, the Tier 1 capital ratio or the Core Tier 1 capital ratio.[47] Once the solvency position under a given scenario has been calculated, a useful metric on which to assess the capital adequacy of an institution under stressed conditions is the capital

Chart 14 Schematic overview of solvency calculation



Source:

47 *Tier 1 capital* is composed of core capital, which primarily consists of common stock and retained earnings, and may also include non-redeemable, non-cumulative preferred stock. Total capital is the sum of Tier 1 and Tier 2 capital, where Tier 2 capital represents supplementary capital including undisclosed reserves, revaluation reserves, general loan loss reserves, hybrid debt and subordinated debt instruments. *Core Tier 1 capital* refers to the core capital of the bank.

shortfall given a minimum threshold for the solvency ratio. The solvency ratio threshold is typically in line with the requirements of national authorities or the EU Capital Requirements Directive. This benchmark determines the potential need for recapitalisation.

Another important factor is data consolidation at the level of banking groups. Using the input from the other modules, the solvency calculation can be done on a consolidated basis, a solo-entity basis or for domestic/foreign subsidiaries only. To compute the capital shortfall for participating banking groups in the latter cases, a consolidation is necessary, along with all caveats such as ring fencing, minority interests, or other regulatory requirements.

2.4 REVERSE STRESS TEST

One of the main uses of the top-down forward-looking solvency analysis tool is to assess the banking sector's resilience to a variety of different systemic risks that form specific scenarios. A key challenge with this approach, however, is to assess the probability of occurrence of different (and often multi-faceted as well as interrelated) scenarios in a comparable manner. This makes it difficult to clearly rank scenarios, as it requires simultaneously evaluation of the impact on banking sector solvency, the overall severity of the scenario configuration and its probability of occurrence. To overcome these obstacles, reverse stress testing methods are employed that allow for comparing and assessing the severity of scenarios conditioned upon the impact of banks being stress tested.

Specifically, reverse stress-testing as applied in the forward-looking solvency analysis framework quantifies how much stronger a given scenario configuration needs to be in order to drive a certain number of banks below a pre-defined capital ratio threshold (e.g. a 6% Core Tier 1 ratio threshold).[48]

Once a scenario is designed and processed using the stress testing framework tools, it is possible to backward engineer the shock sizes that would be needed to generate the result of, for example, a certain number of banks falling below the capital ratio threshold. This approach allows a ranking of adverse scenarios by means of multiples. Multiples are simple factors applied to the initial shocks, which then feed through macro-financial models and additional satellite models into banks' balance sheets. They are reversely calculated so as to match a pre-defined threshold capital measure.

Importantly, a reverse stress-testing procedure requires all modules used for scenario generation, shock translation by means of macro-financial models, and satellite models that link the scenario to balance sheets and profit and loss components to be technically fully integrated. Practically speaking, a manual change of an input parameter (a shock) can thereby be translated immediately through all models into the solvency position of a set of banks. Technical integration is crucial because reverse stress-testing envisages some form of optimisation and goal seeking.

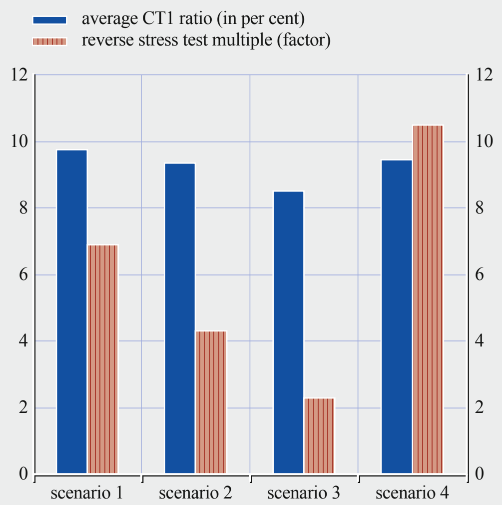
As an illustration, Chart 15 shows the average Core Tier 1 (CT1) ratios of a sample of banks under four different hypothetical adverse scenarios.[49] It also shows the reverse stress test multiples indicating how much stronger the various scenarios need to be in order to bring a certain number of banks below a pre-specified capital ratio threshold (in this case, one-third of the banks below a 6% CT1 capital ratio). The chart shows that scenario 3 is clearly the most adverse, both in terms

48 Notably, reverse stress testing in the top-down stress testing framework should not be mistaken for reverse stress testing carried out at individual banks with their micro-prudential supervisors. Such bank level stress tests usually aim at identifying the specific set of shocks/risks that are serious enough to bring the bank to default.

49 In contrast to the other illustrations in this paper, Chart 15 is unrelated to the baseline and adverse scenarios described above and is based on purely illustrative scenarios.

of end-sample average bank CT1 ratios and in terms of overall severity measured by the very low multiple needed to drive one-third of the banks below the threshold CT1 ratio. At the same time, it is noticeable that a relatively low end-sample average solvency ratio does not necessarily translate into a small reverse stress test multiple. For example, the end-sample average CT1 ratio is smaller under scenario 4 than under scenario 1. However, the reverse stress test multiple is substantially lower under scenario 1 compared to scenario 4. This would typically be an indication of considerable differences in the composition of banks being severely affected by a given scenario.

Chart 15 Illustration of reverse stress test multiples



Sources: ECB and ECB calculations.

2.5 CONTAGION AND FEEDBACK ANALYSIS

Macro stress test exercises (especially supervisory ones) typically end once the "first-round" impact on the stressed banks' solvency position is derived. However, in reality it is to be expected that banks' would react to stressed situations by adjusting their balance sheets in certain ways, which in turn could have ramifications on the real economy and on other banks in the system.[50] For example, the deterioration of the solvency situation (or even failure) of some banks under a stress scenario could give rise to negative contagion effects on other banks in the system, either through their direct bilateral linkages or more indirectly through confidence effects. To analyse such effects, financial network analysis tools are usually applied. At the same time, a typical reaction of banks faced with capital shortfalls to a given target (or minimum requirement) would be to at least partially adjust their asset side.[51] Such actions, for example in the form of loan supply restrictions, could be expected to have real economic implications which would tend to amplify the original adverse macroeconomic scenario. To account for such feedback effects linking results from the stress testing framework to the broader economy requires macroeconomic models with financial sector interfaces that can derive the macroeconomic implications of (solvency) shocks hitting the banking sector.

2.5.1 NETWORK ANALYSIS

The 2007-09 financial crisis and subsequent euro area sovereign debt crisis illustrated that shocks to one part of the financial sector, if severe enough, can easily spill over to other parts of the system and to the wider economy. Tools to assess financial contagion are often rooted in network analysis (see also Box 3 surveying the literature on financial contagion). This section describes a number of network tools developed for the analysis and assessment of financial contagion, and especially how

50 There are practical reasons why supervisory stress tests tend to only include first-round solvency effects. The most obvious one is that it would imply asserting certain behavioural assumptions on the participating banks, the validity of which would be challenging and time-consuming to cross-check for the supervisors. Moreover, assumed dynamic bank behaviour should in turn feed back into the macroeconomic scenario and give rise to a second (or several) stress test iteration to be conducted by the banks. This could be costly and burdensome for the participating banks.

51 See e.g. Berrospide and Edge (2010), Francis and Osborne (2012), Maurin and Toivanen (2012) and Schepens and Kok (2012).

they can be linked to the analysis derived using the forward-looking solvency analysis framework. The range of tools applied at the ECB for these purposes range from exposure-based interbank network models and financial account-based cross-sectoral network models to market data-based spillover models.

Box 3

LITERATURE ON FINANCIAL CONTAGION[1]

Financial contagion can be interpreted as the transmission of shocks between financial market participants resulting from a shock / disruption initially limited to a relatively small number of institutions (Allen and Gale, 2000; de Bandt and Hartmann, 2000; Upper, 2007). Allen and Gale (2000) introduce a concept of financial fragility showing that interlinkages "work well as long as there is enough liquidity in the system" but can transmit problems if there is an excess demand for liquidity. Although the financial links have a positive impact on risk diversification and sharing through flexibility and monitoring (Rochet and Tirole, 1996), Allen and Gale (2000) note a generally high propensity of financial systems to be affected by shocks and observe a non-monotone relationship between the density of network connections and how broadly contagion is spread throughout the network.

To detect and measure financial contagion risk, researchers have adopted approaches from other, seemingly distant research areas such as biology, communication or physics. However, transposition of these approaches to financial networks is far from straightforward due to the behavioural complexities of financial agents.

Financial contagion can take many forms of transmission. For instance, it can be transmitted via direct channels, such as via bilateral exposures (see e.g. Eisenberg and Noe, 2001), via protection selling and buying (e.g. Heise and Kühn 2012; Hałaj, 2013b), via common exposures due to overlapping portfolios (Caccioli et al., 2012) or via other indirect channels (e.g. information contagion, correlation, behavioural commonalities; see Kodres and Pritzker, 2002; Acharya and Yarulmazer, 2008; Acharya et al., 2012a). Furthermore, financial contagion may engulf the financial system at large, but also can affect subsystems of interbank networks (Elsinger et al., 2006; Degryse and Nguyen, 2007) or the payment system (Bech and Garratt, 2006). Ideally, fully capturing potential financial contagion within the financial system requires a 'holistic' approach; for example, using multi-layered network analysis, accounting for interactions and spillovers between different network segments. This would help capture the fact that financial institutions are often linked to each other in wide range of networks and that shocks occurring in one network segment could therefore easily spill over to other network segments, leading to more widespread contagion effects than would be identified when only analysing the different network segments in isolation. Moreover, the events triggering financial contagion can be multi-faceted, ranging from solvency shocks and liquidity shocks to payment system disruptions.

Research related to financial contagion can be grouped in four main strands: static and dynamic statistical models and models of static and dynamic network of flows.

1 Prepared by Grzegorz Hałaj with input from Adrien Amzallag, Maciej Grodzocki and Marco Gross.

Static statistical models are based on graph theory (Réka and Barabási, 2002), percolation (Callaway et al. 2000; Hurd and Gleeson, 2013) or random matrices theory, whereby the contagion potential is identified with a view to the topological properties of networks. Some basic ways to gauge the topological properties of networks and detect 'important' nodes and linkages, such as degree, betweenness or clustering, are based on the statistical properties of networks originally observed in social sciences (Freeman and Hannan, 1977), biology (Dodds and Watts, 2005) or transportation (Nagurney and Liu, 2007). Recently, some measures adopted from internet search algorithms have been used in the financial network context (e.g. DebtRank, inspired by the Google PageRank feedback centrality measure; see Battiston et al., 2012b).

Nevertheless, various types of nonlinearities in network contagion (Allen and Gale, 2000; Amini et al. 2012; Acemoglu et al., 2013) make it difficult to detect and measure the scope and size of contagion simply based on topological measures. Topological structures also do not have direct implications as far as the severity of contagion is concerned. For example, complete networks are perceived as bringing beneficial diversification, but a large enough shock can be more widely spread in such a "complete" system. In reality, however, it is more common to observe core-periphery types of networks for which large, highly connected nodes (hubs) are critical in the spread of contagion, while other nodes can serve as either shock absorbers or shock amplifiers.[2]

A second strand in the literature employs *time-series model methodologies*, and is primarily based on market data such as stock prices, credit default swap spreads, interest rates, etc. Analyses based on time-series model methods proceed by first estimating a model in order to capture observed dependencies across endogenous variables, as well as with respect to exogenous common factors (including, potentially, fundamentals). Some early studies attempted to capture contagion using event studies to detect the impact of bank failures on stock (or debt) prices of other banks in the system.[3] The evidence from these studies was, however, rather mixed. This may be due to the fact that stock price reactions typically observed during normal periods do not capture well the non-linear and more extreme asset price movements typically observed during periods of systemic events, where large-scale contagion effects could be expected. In this light, some more recent market data studies have applied extreme-value theory to better capture such extraordinary events.[4] In a similar vein, Polson and Scott (2011) apply an explosive volatility model to capture stock market contagion measured by excess cross-sectional correlations. Other studies have tried to capture the conditional spillover probabilities at the tail of the distribution by using quantile regressions.[5] Diebold and Yilmaz (2011) propose in turn to use variance decompositions as connectedness measures to construct networks among financial institutions based on market data.[6]

The third group of models analyses *the flow of payments in the system*. Cascade models (e.g. Nier et al., 2008; Degryse et al., 2010; Upper, 2007; Gai and Kapadia, 2010; Hałaj and Kok, 2013a) with more detailed, yet static models of balance sheets analyse sequences of defaults typically using the interbank clearing payments approach (Eisenberg and Noe, 2001), which envisages the

2 See e.g. Furfine (2003), Cajueiro and Tabak (2007), Elsinger et al. (2006), Upper and Worms (2004), Hałaj and Kok (2013).
3 See e.g. Aharony and Swary (1983), Peavy and Hempel (1988), Docking et al. (1997), Slovin et al. (1999), Cooperman et al. (1992), Smirlock and Kaufold (1987), Musumeci and Sinkey (1990), Wall and Peterson (1990), Kho et al. (2000) and Forbes and Rigobon (2002).
4 See e.g. Longin and Solnik (2001), Hartmann et al. (2004), Hartmann et al. (2005) and Gropp et al. (2009).
5 See e.g. Cappiello et al. (2005), Engle and Manganelli (2004), White et al. (2010) and Adrian and Brunnermeier (2009).
6 See also Alter and Beyer (2013) and Gross and Kok (2013a) for some recent applications in this direction analysing contagion between euro area sovereigns and banks.

equilibrium (instantaneous) resolution of payments. Some models try to explain the behavioural foundation of the linkages through game theoretical formation of networks (Jackson, 2010; Cohen-Cole et al., 2010; Acemoglu et al., 2013). The disturbances of the payments can be further exacerbated by shock amplifiers such as liquidity effects, spiral effects of fire sales, information spreading (Cifuentes et al., 2005; Adrian and Shin, 2010; Brunnermeier and Pedersen, 2009), or large financial institutions' opaqueness (Flannery, 2010). In recent years, contagion models of this type have become integrated modules of stress testing frameworks for banking regulators and supervisors. As far as the regulatory dimension is concerned, Gauthier et al. (2010) study the impact of capital levels and availability of liquidity sources on mitigating the risk of contagion. The main finding verified in all studies is that the size of contagion related solely to the direct exposures is very limited, insignificant in many examples, and only amplifiers such as fire sales or liquidity shocks can account for the contagion losses in the financial system.

The fourth strand in the literature refers to *models of flows in dynamic networks*. The key differentiating feature of this strand is related to the direct modelling of the evolution of financial institutions' balance sheets, taking into account some important behavioural aspects of banking systems (Iori et al., 2006; Georg, 2011). Notably, agent-based modelling techniques can be very helpful in addressing the complex strategic actions of banks. In that context, assessment of contagion risk requires that some novel dynamic measures of systemic risk are developed, such as the financial robustness index proposed by Battiston et al. (2012a). Moreover, some researchers see unexplored potential for the control theory (Galbiati et al., 2013, Hałaj and Kok, 2013b), which could be used to more precisely and systematically detect important nodes and thereafter mitigate the systemic risk in the whole system by dynamically imposing supervisory actions on particular banks deemed systemic. A stable risk assessment toolkit within this strand of research is still far from being completed.

2.5.2 INTERBANK CONTAGION MODELLING

One specific outcome of a macro stress test is the number of firms which would not be able to comply with pre-defined solvency requirements under stressed conditions. In the absence of any remedial measures (such as issuing new equity or state capital injections) to fill the resulting capital gaps, the banks "failing" the stress test could in turn be expected not to be able to repay their creditors in the interbank market, thus triggering losses at other banks via direct bilateral exposures among banks.[52] Losses incurred on defaulted interbank assets, if large enough, may cause defaults of interbank creditors; consequently, these may not be able to fully meet their own interbank obligations on time, triggering a cascade of default in the system. In order to capture this mechanism, a network of exposures has to be estimated, an initial shock to the system has to be specified and an algorithm of loss transmission has to be developed in order to measure the risk, magnitude and scope of contagion.[53]

A practical challenge for studying interbank contagion is that the availability of data necessary for constructing the relevant interbank network is usually very limited; especially on a timely basis. Ideally, a matrix of transactions should be defined, taking into account volumes, types of assets and maturity structure. Since networks exhibit very volatile patterns, a representative time series

52 Interbank contagion need not only occur via the direct bilateral exposures but can also be transmitted via more indirect confidence-type effects, whereby for example shocks to one bank increase the funding costs of other system banks; see e.g. Battiston et al. (2012a).

53 *Risk* is the probability that shocks can be transmitted between financial institutions, e.g. the default of one bank implies financial problems for other banks. *Magnitude* refers to the size of contagion losses. *Scope* informs about how many institutions can be affected if contagion occurs.

of such matrices should be analysed. The interbank exposure data should accurately reflect the market conditions (general funding conditions, credit risk accumulated in the financial system, etc.) corresponding to the analysed period. Supervisory databases frequently contain snapshots of the interbank networks, which can be reconstructed from the reported bilateral exposures, usually as of the end of the year but sometimes on a more frequent basis.[54] Gross settlement systems may provide an especially useful and real-time source of information about the interbank linkages (although networks constructed from such payment system data usually have to be confined to the overnight segment[55]).

Simulation techniques can be helpful to overcome the problem of data scarcity on interbank linkages. The most commonly used are the entropy maximising ones, which estimate the missing links with aggregate data.[56] However, as pointed out by Mistrulli (2011), among others, maximum entropy approaches tend to produce too much averaging at the tails of the distribution of potential networks and therefore may underestimate contagion risk.[57] To overcome the deficiencies related to maximum entropy measures and to circumvent the typically volatile nature of point-in-time interbank network snapshots, Hałaj and Kok (2013a) developed an alternative algorithm to randomly generate various possible EU interbank structures. This random network generation mechanism is derived from a constructed map of probabilities that two banks are interconnected, which in turn is based on individual bank aggregate balance sheet information and interbank linkages inferred from the geographical breakdown of exposures.[58] Notably, the geographical dimension of the model allows for analysis of the cross-border interlinkages (see Chart 16).

Losses related to the direct exposures (triggered by insolvency, illiquidity or disruptions in the payment systems) can be further exacerbated by banks trying to liquidate their assets in order to fulfil their obligations. Such fire sale effects, or liquidity spirals, are part of some contagion models and are also reflected in the framework.[59] In the model, fire sale losses are triggered by the assumption that banks sell part of their securities' portfolios in order to cover the gap between the expected and realised inflow of interbank payments. The depth of asset devaluation depends on the aggregate volume sold by banks in the network.

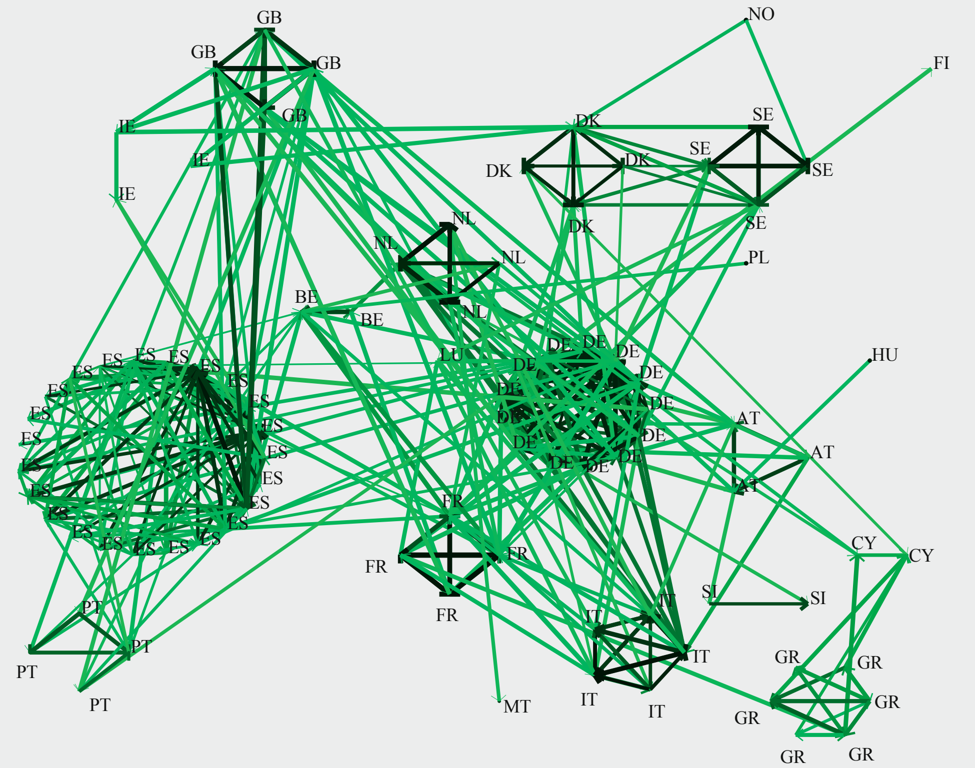
To study the transmission of solvency shocks among EU banks (derived using the top-down stress testing tools), the interbank structures obtained via the simulated network approach are then used to measure the distribution of interbank losses transmitted via the simulated networks, after an assumed default of a group of banks.

The current framework of interbank contagion is largely based on a mechanical and rather static loss-cascading mechanism. Nevertheless, the incorporation of dynamic and behavioural aspects of banks' participation in the interbank market is key to capturing the network formation and contagion in a more realistic setting. One analytical avenue to achieve the goal of a more comprehensive interbank contagion model is to apply so-called agent-based modelling, with optimising banks dynamically interacting in the network.[60] Other enhancements will include multi-layered network

54 See e.g. Furfine (2006), Elsinger et al. (2006), van Lelyveld and Liedorp (2006), Hałaj (2007), Cajueiro and Tabak (2007) and Mistrulli (2011).
55 Where the advance and repayment legs of bilateral transactions can be easily matched. When expanding to longer maturities, such matching becomes much more challenging.
56 The estimation techniques, such as entropy maximisation and RAS algorithm, and their applications are described e.g. in van Lelyveld and Liedorp (2006).
57 At the same time, Mistrulli (2011) also finds that for specific banking structures the maximum entropy method can lead to an overestimation of contagion risk.
58 The tool is flexible enough to incorporate other data sources if available.
59 See e.g. Cifuentes et al. (2005), Brunnermeier and Petersen (2009) and Gauthier et al. (2010).
60 See Hałaj and Kok (2013b).

Chart 16 Simulated network of interbank linkages among a sample of EU banks

(net percentage of reporting banks)



Source: Hałaj and Kok (2013a).
Note: the darker the line, the higher the probability of a link between the two given banks.

approaches to account for the fact that banks are interconnected in many different market segments at the same time (e.g. uncollateralised interbank market, collateralised interbank market, CDS counterparty exposures, etc.), and that shocks to the network in one segment can easily spill over to other segments.[61] In other words, the objective is to operate with a "holistic" approach to modelling interbank contagion. Finally, a comprehensive modelling of interbank contagion can be a useful element for the calibration and assessment of macro-prudential policies aimed at limiting contagion risk. Examples of such policies could be varying large counterparty exposure limits or adjusting the systemic risk capital surcharges embedded in the Basel framework to ensure that sufficient capital is set aside to cover counterparty risks (see Hałaj and Kok, 2013b).

2.5.3 CROSS-SECTORAL SPILLOVER ANALYSIS

The global financial crisis and subsequent euro area sovereign debt crisis have illustrated the potential spillovers both across countries and across economic sectors and the need to better understand these linkages and vulnerabilities. It has been argued that the growing interconnectedness of the various sectors of the economy (e.g. non-financial corporations, households, financial intermediaries and governments), both at national and international levels, itself determines the speed and scope of loss propagation throughout the globe (Castrén and Rancan 2013, Dudley 2009, Stiglitz 2008). Against

61 See Montagna and Kok (2013).

this background, this section describes the basic approach to conducting cross-sectoral spillover analyses currently applied in the ECB's risk assessment analytical framework.[62]

Data

The starting point of the cross-sectoral spillover analysis is the financial (as opposed to non-financial) balance sheets of the different sectors of the economy. These balance sheets are generally referred to as sector accounts (or 'flow of funds'), and are available for many OECD countries on an annual and quarterly basis. The Euro Area Accounts (EAA) dataset, published jointly by the ECB and Eurostat on a quarterly basis, contains data for each euro area member starting from its accession date. The sectors covered are households (HH), non-financial corporations (NFC), monetary and financial institutions (MFIs), insurance corporations and pension funds (ICPF), other financial intermediaries (OFI)[63], general government (GOV), and the rest of the world (RoW), in line with the European System of Accounts 1995 (ESA 95). An attractive feature of the dataset from a financial contagion point of view is that the data cover the entire economy of the country in question, meaning that the aggregate assets must equal aggregate liabilities.[64] In other words, it forms a closed and internally consistent system, which means that each financial asset item of a sector has a counterparty item on the liability side of some other sector.[65]

Network estimation

The second necessary component of a cross-country/cross-sectoral analysis is a profile of the linkages between each sector (commonly referred to as 'who-to-whom' linkages). In the case of the EAA, these linkages already exist for loans, at the country level (e.g. Austrian MFI loans to Austrian households), as well as deposits (e.g. from Austrian MFIs to German MFIs) and the securities and equity holdings of MFIs (e.g. Austrian MFI holdings of Austrian NFC securities). However, the rest of the network structure must be estimated for the remaining items.[66] The current setting uses a maximum entropy approach to create the cross-sectoral interconnections missing in the data.[67] Chart 17 provides an illustrative example of the cross-sectoral interlinkages within euro area countries, also allowing for cross-country spillovers via cross-border banking system-wide interconnections.

The resulting network structure can then be analysed in terms of standard network structure measures, including degree, betweenness and closeness. Furthermore, the user can look at the evolution of these measures over time, as is done for example in Castrén and Kavonius (2009) and Castrén and Rancan (2013), who show the increasing interlinkages among the euro area in the lead-up to the global and subsequent euro area crises, followed by some reduction in the complexity due to adaptations in banking models, as well as lingering concerns over banks in countries with stressed sovereigns.

62 The methodology applied is primarily based on Castrén and Kavonius (2009).

63 Other financial intermediaries (OFI) include institutions engaging in financial intermediation by incurring liabilities in forms other than currency, deposits, or insurance/pension-type obligations. They also include 'financial auxiliaries', which only facilitate financial intermediation and do not set themselves at risk by acquiring financial assets or incurring liabilities (for example brokers, investment managers, and venture capital firms).

64 According to the ESA95 principle, all data are valued at market prices or as close to the market price as possible in cases where these are not readily available (for example, loans or insurance/pension fund technical reserves).

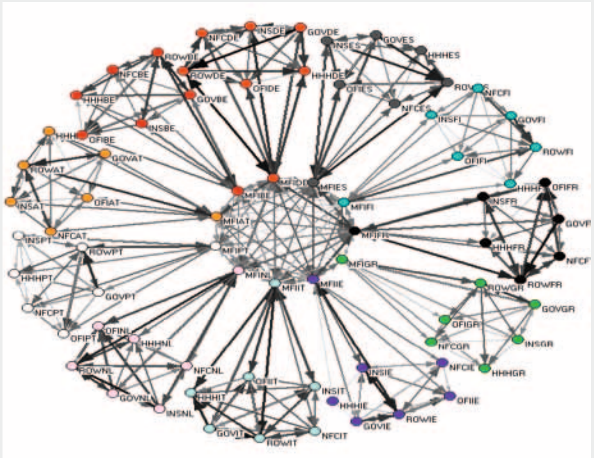
65 See Castrén and Kavonius (2009) for an applied discussion and graphical illustration of a sectoral balance sheet. Further background on the production and structure of the euro area accounts can be found at http://www.ecb.europa.eu/stats/acc/html/index.en.html.

66 It is important to note that the EAA data are unconsolidated, implying that sectors can be assumed to have assets/liabilities with themselves, for example inter-MFI (interbank) deposits.

67 See also Blavarg and Nimander (2002), Wells (2004), Degryse and Nguyen (2007), van Lelyveld and Liedorp (2006), and Castrén and Rancan (2013).

Chart 17 Stylised network of cross-sectoral linkages within the euro area

(net percentage of reporting banks)



Source: Castrén and Rancan (2013).
Note: The darker the line, the higher the probability of a link between the two given sectors.

Shock approach and outputs

The network can then be applied to explore the system-wide effect of stress in one or several sectors. The simplest approach to doing this involves imposing a shock to a variable(s) in a particular sector(s) and tracing through the expected losses from one sector to another, assuming that losses must be immediately recognised on the affected sectors' balance sheets. These losses accrue in the form of a reduction in asset holdings which, via the above accounting assumption, must be immediately passed through to equity values on the liability side. This equity represents an asset for another sector or sectors, and thus the reduction in equity of the first-hit sector becomes a further loss for the second-hit group(s). The process continues until no further losses are estimated. In this framework, an end to the process is guaranteed due to the fact that the household and government sectors merely absorb equity losses but do not transmit them further, since they do not issue equity.

The ECB makes use of such a cross-sectoral framework as part of its overall systemic risk assessment, typically beginning with a shock to bank equity (via the losses incurred under adverse scenarios in the stress test). As a result, sectors holding equities of the banking sector also suffer losses, in proportion to these equity holdings. Non-banking sectors' own losses are reflected in their own equity value, which subsequently spreads to all types of equity holdings across the sectors as discussed above. The process is repeated for each euro area country in order to gauge which country's MFI sector causes the most systemic damage from defaulting on its obligations to another particular country.

2.5.4 FINANCIAL MARKET DATA-BASED CONTAGION

In contrast to the balance sheet-based simulations described in Sections 2.5.2-3, financial contagion can also be captured by employing financial market data.[68] Commonly used techniques to analyse market data-based financial contagion include *autoregressive conditionalheteroscedasticity* (ARCH) and *generalised autoregressive conditional heteroscedasticity* (GARCH) type models

68 In an early contribution, Forbes and Rigobon (2002) defined financial market data-based contagion as a significant increase in cross-market linkages in response to a shock.

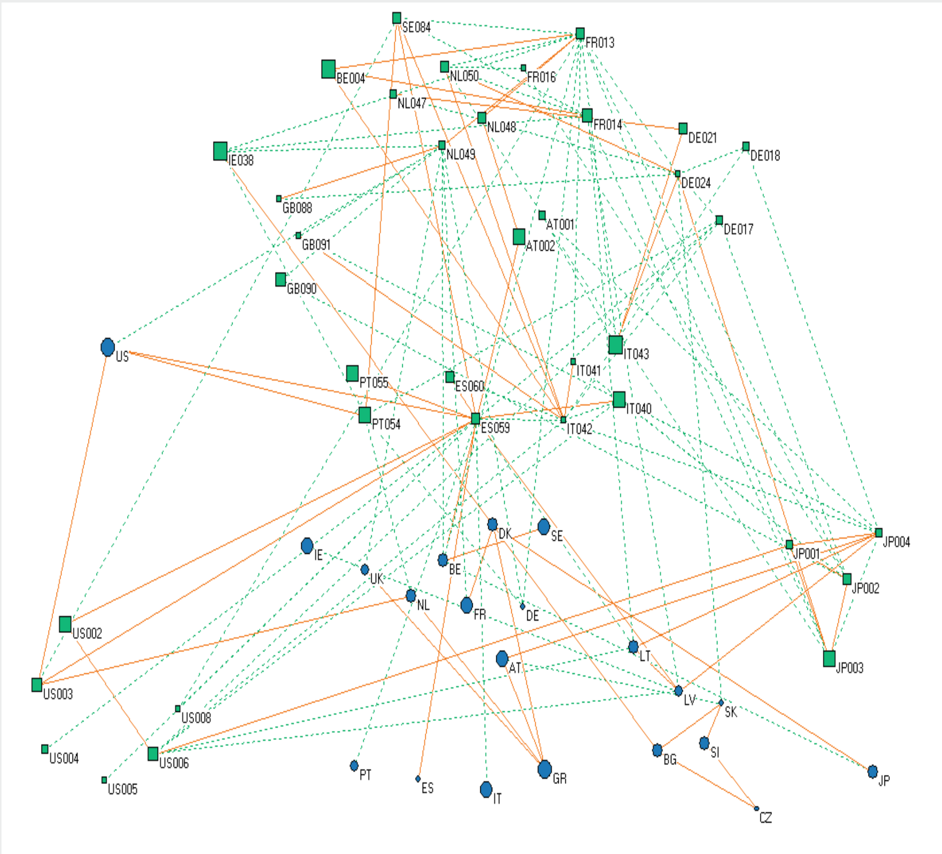
(Hamao et al., 1990), error correction models (Longin and Solnik, 1995), *vector autoregressive* (VAR) models (Diebold and Yilmaz, 2012; Alter and Beyer, 2012) and *global vector autoregressive* (GVAR) models (Gray et al., 2013; Gross and Kok, 2013a).

A distinction can be made between direct, observed dependences captured by the models' coefficients and indirect, contagion potential due to the correlation of shocks (the residuals of the model). Observed dependences and excess correlation of shocks might change over time, implying varying levels of contagion potential in the respective segment of the markets that the model addresses. A concept that also belongs to the time-series model category is the Conditional Value-at-Risk (CoVaR) methodology proposed by Adrian and Brunnermeier (2009). The CoVaR measure quantifies how much a financial institution contributes to systemic risk when being assumed to experience distress.

A tool that is part of the ECB's analytical framework, which allows identifying and assessing shock propagation channels is the Mixed Cross-Section Global Vector Autoregressive (MCS-GVAR) model of Gross and Kok (2013a). This framework is used to model credit default swap spreads for

Chart 18 Network visualisation of the MCS-GVAR model of bank and sovereign CDS spreads in the EU, the US and Japan

(net percentage of reporting banks)



Source: Gross and Kok (2013a).
Note: Sovereign nodes are blue, bank nodes are green. The size of the nodes is proportional to the average impact (measured by maximum adverse responses) of banks/sovereigns on the overall system obtained in a systematic shock simulation. The threshold p-value for displaying connections was set to 85%.

sovereigns and banks and is well suited to studying the transmission of shocks across banks and countries since it allows for endogenous feedbacks both within and across the two cross-sections.[69] The tool can be employed to analyse spillover potential between banks and sovereigns, as visualised in Chart 18. From a stress testing perspective, it can be employed both for estimating contagion arising from (stress test-induced) shocks to specific banks and for scenario simulation. With regard to the latter, the tool can be linked to the financial shock simulator tool (described in Section 2.1.2), for example to generate shocks to individual banks' CDS spreads (a measure of their wholesale funding costs) following simulated shocks to sovereign CDS spreads.

2.5.5 MACROECONOMIC FEEDBACK EFFECTS

As mentioned above, realistically it should be expected that a stress scenario which has negative implications for the solvency positions of banks would cause banks to respond to the shocks, which could in turn result in second-round impacts on the macroeconomic environment, further amplifying the initial shocks hitting the banking sector.

To quantify the repercussions of a shock to the banking sector on the real economy requires models with adequate real-financial linkages. For this kind of analysis, two broad approaches are pursued at the ECB: first, the feedback effects between macroeconomic and financial variables can be analysed using Dynamic Stochastic General Equilibrium (DSGE) models, which are structural models since they build on micro-foundations, i.e. on optimising behaviour of (rational) economic agents; second, reduced-form econometric models can be employed which can be large scale, while not relying on any specific underlying structural assumption about the behaviour of agents.

Linking bank balance sheet analysis with large-scale DSGE macro models embedding a constrained banking sector

One approach to assess the second-order impact of shock scenarios on banks' solvency is to apply DSGE models embedding a realistic characterisation of a banking sector facing capital constraints. One such model available at the ECB is the DSGE model by Darracq Pariès et al. (2011), which is a closed-economy estimated DSGE model for the euro area, with financially-constrained households and firms encompassing an oligopolistic banking sector, and features frictions for both credit demand and supply.[70]

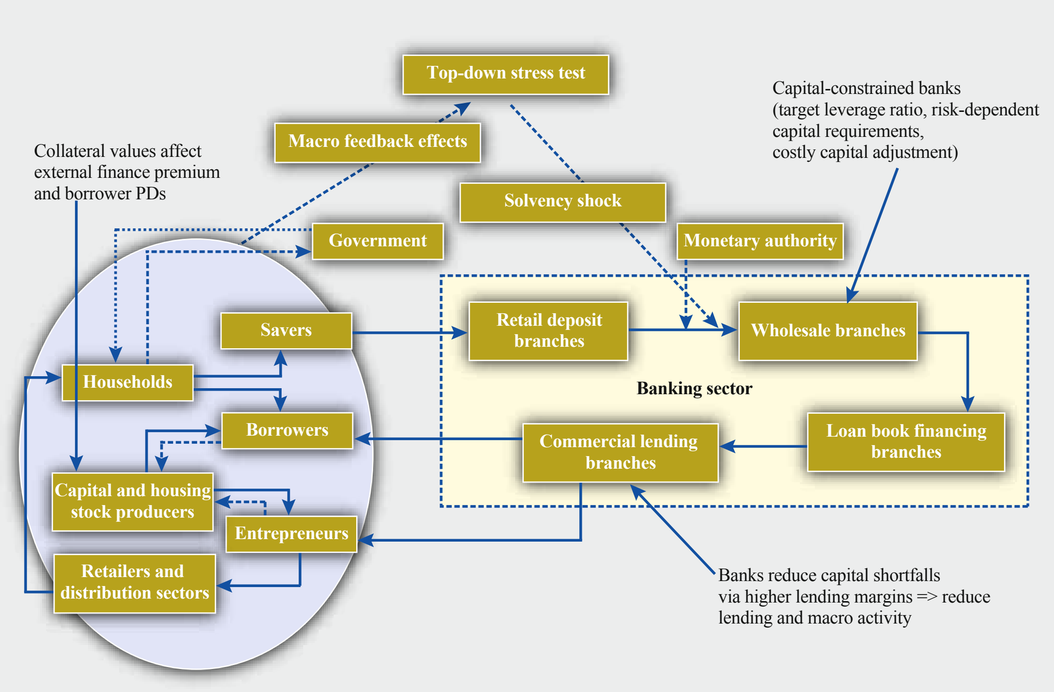
This setup allows an examination of the extent to which frictions to credit demand and supply amplify shocks to the economy and how they affect the monetary policy transmission mechanism. Moreover, the model is well suited to assessing the macroeconomic implications of shocks to bank capital and the implications of introducing more stringent capital requirements. Furthermore, the model can be used to shed light on the potential effects of active macro-prudential policies over the cycle and their interaction with monetary policy.[71]

69 Systematic shock simulations of the estimated MCS-GVAR model allow detecting and ranking the banks and sovereigns that are most vulnerable to shocks arising elsewhere in the system, respectively according to how influential they are in exerting impact on the system. Moreover, systematic shock simulations are conducted to generate an Index of Spillover Potential that summarises in one measure the spillover potential within and across the two cross-sections and suggests the extent to which banks and sovereigns are connected.

70 In the model, the banking sector collects deposits from patient households and provides funds to entrepreneurs and impatient households. Three layers of friction affect financial intermediaries. First, wholesale bank branches face capital requirements as well as adjustment costs related to their capital structure. Second, nominal stickiness generates an imperfect pass-through of market rates to bank deposit and lending rates. Third, due to asymmetric information and monitoring costs in the presence of idiosyncratic shocks, the credit contracts proposed to entrepreneurs and impatient households factor in external financing premia which depend indirectly on the borrower's leverage. Other prominent recent studies which include a banking sector in a DSGE framework are Angeloni and Faia (2013), Christiano et al. (2010), Gertler and Karadi (2012) and Gerali et al. (2010).

71 See also ECB *Financial Stability Review*, May 2013, *Special Feature A*. Angeloni and Faia (2013) furthermore provide important insights into how a countercyclical macro-prudential policy can usefully contribute to the policy mix and complement monetary policy in macroeconomic stabilisation.

Chart 19 Interfaces between top-down solvency analysis framework and DSGE model with banking sector



Source: Darracq et al. (2011).

Chart 19 illustrates in a stylised way how the forward-looking solvency analysis derived using the top-down stress testing framework can be fruitfully complemented with a DSGE model. The typical input to the macro model derived from the top-down stress test framework would be a *solvency shock*, usually defined as the end-horizon capital shortfall to a pre-defined capital ratio threshold. As banks in the model are assumed to operate with a target capital level, they have an incentive to increase their lending spreads to accumulate earnings that can be retained and thereby help close the capital gap. The increase in lending spreads will in turn reduce loan demand and ultimately negatively affect spending and investment. The propagation of the solvency shock to the real economy (illustrated by the blue oval in Chart 19) can be fed back to the original macroeconomic scenario considered in the top-down stress test, and a second stress test iteration can be conducted on this basis to calculate the second-round impact on the banking sector.

Alternative outputs from the forward-looking solvency framework that could be used to trigger macroeconomic feedback effects are loan supply shocks (e.g. due to imposed funding constraints triggering asset-side deleveraging) or projected changes to lending spreads. For such configurations, the model by Christiano et al. (2010) would also be suitable for providing relevant macro feedback effects.[72]

72 This is a standard DSGE model estimated on euro area data and extended by including a credit market, bankruptcies, money holding decisions and a liquidity-creating banking sector. The presence of a profit maximising banking sector, extending credit and operating a fractional reserve-based transformation of base money into deposits and issuing short-term securities allows for including a broad array of monetary aggregates and financial prices in the empirical analysis.

Complementary tools to analyse real-financial linkages

As outlined at the beginning of this section, reduced-form macro econometric models, can also be used to assess the real financial inter-linkages. For instance, the ECB's New Multi-Country Model (MCM) for the euro area is a large-scale macro-econometric model with a tight theoretical structure.[73] The model was one of the models used in the Macroeconomic Assessment Group study assessing the transition costs of implementing the Basel III standards.[74]

Another strand of models employed by the ECB consists of Vector Autoregressive models with real-to-financial linkages. For example, the ECB uses the Contingent Claims Analysis[75] Global Vector Autoregressive (CCA-GVAR) model developed by Gray et al. (2013) to study the interactions between the banking system, sovereigns, the corporate sector and the macro-economy across countries. The CCA-GVAR is a model that uses the CCA risk indicators for the banking systems in each country, for the sovereigns and for the corporate sectors, real GDP growth and credit growth to analyse the spillover and contagion effects across sectors and countries in a fully endogenous setting. The model draws on the advantages of the CCA risk methodology, which uses both market data and accounting information and so has a forward looking component and is well suited to capturing nonlinearities of changes in bank assets, equity capital, bank credit spreads, and default probability within and across institutions and sovereigns. The CCA-GVAR model can be applied to simulate scenarios with either individual or joint shock origins to assess how the shocks propagate through the banking system, sovereigns and the corporate sector, and how they influence GDP and credit growth across countries.

Interlinkages between the real and the financial sector can also be examined by means of large-scale Bayesian Vector Autoregressive (BVAR) models, as for example proposed by Giannone et al. (2012). Bayesian techniques envisage the imposition of prior assumptions upon the model parameters, effectively shrinking the parameter space and thereby allowing for estimating large-scale models with a large number of endogenous variables. In this respect, the estimation of BVAR models represents an alternative to the GVAR model approach, with the latter compressing the parameter space to overcome the "curse of dimensionality" by operating with weights. BVAR model estimates and simulation results have proven to reproduce key stylised facts about the joint behaviour of a set of macroeconomic, financial, monetary and credit variables. In the context of the ECB stress-testing framework, BVAR models can be employed to assess the responses of real variables to shocks originating in the financial and credit sectors.

73 The model allows for non-unitary elasticity of substitution, non-constant augmenting technical progress and heterogeneous sectors with differentiated price and income elasticities of demand across sectors. It covers the five largest euro area countries and has the explicit inclusion of expectations on the basis of three optimising private sector decision-making units. The model can be simulated under perfect foresight rational expectation assumptions or under learning expectations where agents optimise their learning based on unknown driving stochastic processes but without uncertainty of the deep parameters – i.e. there is uncertainty concerning the process driving future developments; see Dieppe et al. (2011a) and Dieppe et al. (2011b).

74 See FSB/BCBS (2010).

75 Contingent Claims Analysis (Gray, Merton and Bodie, 2006; and Gray and Malone, 2008), which is a generalisation of the option pricing theory first introduced by Black-Scholes (1973) and Merton (1973), provides a methodology for constructing risk-adjusted balance sheets and estimating forward-looking risk indicators.

Box 4

INSURANCE SECTOR SOLVENCY ANALYSIS FRAMEWORK: A STOCK-TAKING OF AVAILABLE TOOLS[1]

Insurance stress testing – introduction

The insurance sector is of systemic importance to the financial system. Insurers are primary institutional investors, with euro area insurers holding financial assets worth €5.9 trillion (as of end-2012)[2], and their economic behaviour may have a strong impact on the financial markets. During the last financial crisis, insurance companies, especially in the US, were at the epicentre of the crisis.[3] Therefore, the assessment of risks for the insurance sector through stress testing is important from a financial stability perspective.

The literature on insurance stress testing is rather limited and consists mostly of technical notes of supervisors and international organisations. EIOPA, the EU supervisory oversight authority for the insurance sector, conducts regular bottom-up stress tests with scenarios customised for the insurance sector, such as low-yield scenarios (see for example EIOPA, 2012). The IMF has also occasionally conducted top-down insurance stress test exercises in the context of its financial sector assessment programs (FSAPs).[4] Moreover, there is a research strand investigating in a quantitative way the impact of a low interest rate environment.[5] For instance, Kablau and Wedow (2011) assess the effect of a protracted low interest environment on the German life insurance sector using aggregate data and investigating the depletion horizon for bonus and rebate provisions (BRPs).[6] French et al. (2011) use a sample of 50 large insurers to gauge the impact of changes in portfolio yields, separately for life and property/casualty insurance firms.

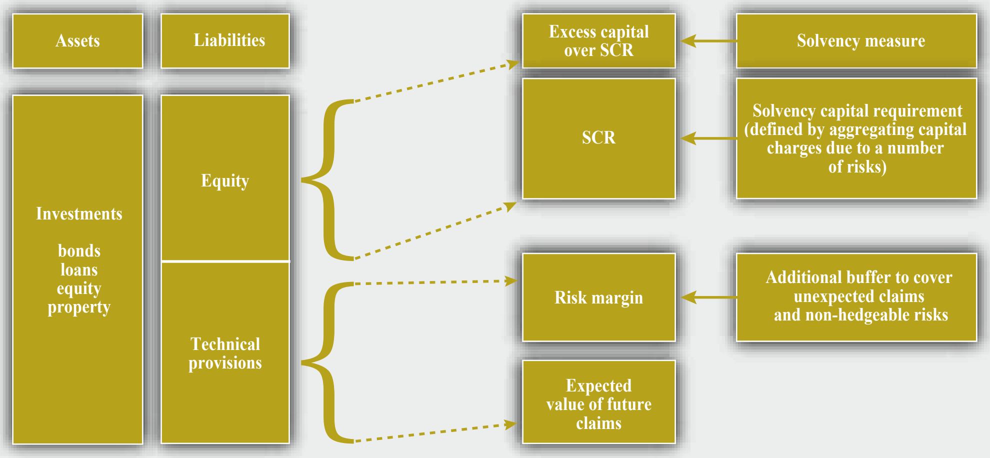
A comparison of insurance versus banking with respect to business model and solvency

Insurance firms offer a variety of insurance services by pooling risks across a large cross section of individuals. Chart A represents a simplified balance sheet of an insurance company. On the liability side, technical provisions represent the present value of future benefit payments to policyholders (Doff, 2011). The premiums received from the insurance contracts are invested and, therefore, the asset side consists primarily of investment assets.

Insurance companies are funded with upfront payments in exchange for future claims, while banks have to fund long-term assets with short-term funds. Insurers usually invest in long-term assets in order to match the duration of their liabilities. In contrast to banks, however, insurers' liabilities are, in general, of longer duration compared to their assets. This implies that funding is not such a pressing concern for insurers as it is for banks.[7] At the same time, this balance sheet composition gives rise to interest rate risk, since a decrease in interest rates will in general

1 Prepared by Angelos Vouldis with input from Patrizia Baudino, Christoffer Kok and Matthias Sydow.
2 According to ECB data: http://www.ecb.europa.eu/stats/money/icpf/html/index.en.html. For a review of the size of the insurance sector relative to the financial sector, across jurisdictions, see BIS (2011).
3 An example is AIG, which required a bail-out from the US government (through lending by the New York Fed) after losses from its exposure to mortgage-backed securities (MBSs) and collateral calls on credit default swaps (CDSs).
4 See for example IMF (2007) for Switzerland, IMF (2011) for Guernsey (top-down stress test, including market as well as insurance-specific shocks), and IMF (2012) for Israel (top-down stress tests, focusing on market risks). Related to insurance stress testing also is Impavido (2008), which presents a methodology for conducting stress tests on defined benefit pension plans.
5 For a discussion of the potential impact of a protracted low interest rate environment on insurance companies, see Antolin et al. (2011).
6 BRPs are actuarial reserves, used primarily for policyholders' profit participation, that represent a buffer to maintain the guaranteed return in case the returns on investment holdings are not sufficient.
7 Except in the case of large unexpected catastrophes.

Chart A Simplified balance sheet of an insurance company (under Solvency II)



Source:

increase the value of liabilities more than the value of assets. Moreover, one of the main risks currently faced by insurance firms is that the low yield on invested assets may not be sufficient to match the promised payments.

The definition of solvency requirements for insurance firms reflects the long-term nature of insurance liabilities. According to the Solvency II regulatory framework planned for implementation in the EU, insurers' capital requirements are determined in a comprehensive way based on the risk profile of undertakings, i.e. solvency is assessed considering the sensitivity to risks of both assets and liabilities.[8] In contrast, in banking, capital requirements are defined by assigning risk weights only to assets and taking into account the relation of risk-weighted assets to available capital, while banks' funding side (liabilities) is treated separately in Basel III via the liquidity requirements.[9]

Insurance stress testing tool

The ECB top-down insurance stress testing tool aims for a quantified assessment of the potential impact on euro area insurers of the main systemic risks at a given point in time. The assessment relies on a market-consistent approach to the quantification of risks and, thereby, ignores the heterogeneity of current institutional settings and accounting practices among jurisdictions.[10] The current version of the tool includes the market valuation impact of stressed conditions on both the assets and liabilities of insurance corporations (for a recent application, see the ECB *Financial Stability Review*, May 2013). In addition, rather than trying to gauge the impact in terms of prudential solvency ratios, the approach aims at spelling out the main risks in economic terms.

8 Consequently, the estimation of the solvency position (e.g. under a Solvency II regime), from a top-down perspective is much more difficult for insurance compared to banking.
9 For a detailed comparison between Solvency II and Basel III, see O'Shea (2013).
10 For an overview of insurers' current accounting practices and trends, see Swiss Re (2012).

Finally, given that the definition of the forthcoming Solvency II regime has not yet been finalized,[11] the tool makes it possible to gauge the impact of different regulatory specifications, such as the discount rate used to value liabilities and the use of countercyclical premiums.

The insurance stress testing tool implements a top-down approach, estimating the impact of a macroeconomic scenario on the balance sheet of insurance firms.[12] Specifically, the impact of a scenario can be represented as a percentage of assets (providing a generic measure of impact size) or of net assets[13,14] (providing a measure of solvency impact).

The results are derived by using publicly available data based on euro area insurers' financial reports and is therefore not based on confidential supervisory information. The sample currently covers 13 large insurance groups in the euro area.

A number of simplifying assumptions are currently made for the insurance stress testing exercise. First, available granular data (e.g. on investment in sovereign bonds, broken down by jurisdiction; on investment in corporate bonds and on loans, broken down by credit ratings; and on liabilities and debt assets, broken down by maturity) are used wherever possible, but broad aggregates of financial investments have to be used in some instances. Second, no hedging or other risk-mitigation measures[15] are taken into account, which implies that losses might be overestimated. Third, all income and expenses related to the underwriting business are assumed to be fixed. For example, reduced demand for insurance products is not taken into account and each maturing contracts is expected to be replaced, so that the underwriting income of each insurer remains constant.[16] The underwriting component of income is stressed only in the form of increasing lapse rates.[17]

In the current top-down framework, the risks for insurers are transmitted through three broad channels, namely: (i) valuation effects on financial securities and liabilities owing to changes in sovereign yields and swap rates; (ii) sales of assets due to unforeseen payments originating in increased lapse rates and (iii) changes in the credit quality of loan portfolios. In addition, related to the low-yield environment discussion, a separate module quantifies the effect on total investment yields resulting from a shock to the yields of reinvested assets.

The impact of bond yield changes is calculated on both the asset and the liability side of insurers' balance sheets. Specifically, sensitivities to interest rate changes are computed for each interest-rate-sensitive asset and liability exposure. The relevant yield curves are used to project asset and liability cash flow streams, to calculate internal rates of return, and then to discount the cash flows using yield curve shocks. Haircuts for debt securities are derived from changes in the value of representative securities implied by the increase in interest rates under each scenario. Valuation haircuts to government bond portfolios are estimated on the basis of representative

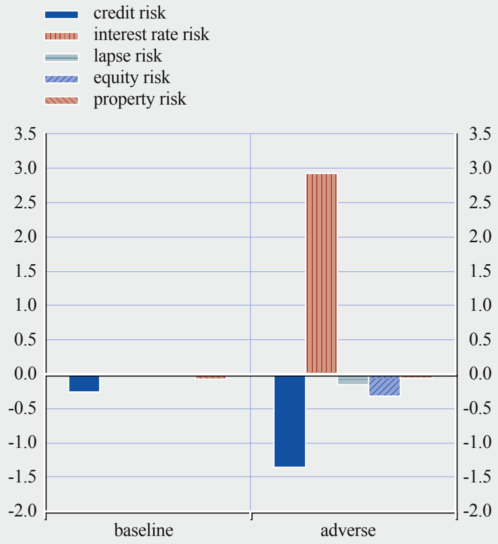
11 For the latest quantitative impact study (QIS5) aimed at calibrating Solvency II, see EIOPA (2011).
12 The applications of the tool are not related to the EU-wide stress tests in the banking and insurance sectors coordinated by the EBA and the European Insurance and Occupational Pensions Authority (EIOPA), respectively.
13 Net assets are defined as assets minus liabilities.
14 Broadly corresponding to the available solvency margin (ASM), which is the current EU capital adequacy criterion for insurance companies.
15 For example, interest rate-risk hedging, asset-liability matching techniques and counter-cyclical premia (to dampen the effect of temporary adverse interest rate shocks through offsetting changes in the valuation of liabilities).
16 In other words, a static portfolio of contracts is assumed in which maturing contracts are replaced in a way that keeps current and future cash flows unchanged.
17 The lapse rate is defined as the fraction of contracts prematurely terminated by the policyholders.

euro area sovereign bonds across maturities. Haircuts for corporate bonds are derived from a widening of credit spreads.[18] Finally, shocks to stock prices and property prices are applied uniformly across insurers.[19] These haircuts are applied uniformly across the sample of large euro area insurers.

Lapse risk is quantified by projecting insurers' cash flows over a given horizon, assuming a static composition of contracts and the reinvestment of maturing assets without any change in the asset allocation. Lapse rates are linked to macroeconomic variables.[20] Additionally, unexpected lapses are assumed[21] and lead to surrender payments.[22] In cases where surrender payments lead to negative cash flows, the insurer is obliged to use cash reserves or sell assets to meet these obligations. The lapse risk equals the cash or other assets that is needed to cover surrender payments.

Chart B Asset value changes for large euro area insurers under different scenarios

(Q4 2012 - Q4 2014; percentage of total assets)



Sources: ECB, firms' financial reports and ECB calculations.

The credit risk assessment of loan portfolios is carried out using i) breakdowns by rating or region, depending on data availability, and ii) loss rate starting levels, which are stressed using the same methodology as applied for assessing the resilience of euro area banks.

As an illustration, in Chart B the average impact from the materialisation of macro-financial risks under a baseline and an adverse scenario are presented.[23] Under the adverse scenario, insurers' losses mainly originate from credit risk. The primary component of credit losses originates from corporate debt investments.

By contrast, the rising yields projected under the adverse scenarios do not have an adverse impact on the economic solvency of the insurers in the sample. In fact, net assets increase on average due to the longer duration of liabilities and, consequently, their greater sensitivity to the applied discount rate.[24]

18 Credit spreads are set by simulating a joint, multivariate forward distribution of daily compounded changes in various iTraxx indices with a 60-day horizon.
19 Property prices react endogenously to other elements of the macro-financial scenario.
20 Specifically, sensitivities of lapse rates to GDP and unemployment were derived by taking the mean of a number of elasticity values, collected from the literature (e.g. Honegger and Mathis, 1993; Kim, 2005; Smith, 2004) and from ECB calculations.
21 The unexpected component of lapses is defined as the difference between the projected lapse rate and the average lapse rate reported by large European insurers.
22 It is assumed that 50% of the total amount represented by the extra lapse rates has to be paid (due to the existence of penalties in the contracts, which lower the insurers' risk).
23 The impact is very heterogeneous across individual insurance groups.
24 Regarding interest rate risk, the forthcoming Solvency II regime is expected to replace the current practices with a uniform approach consisting of using the swap curve as a discount rate. To gauge a rough impact of such a regime, a projected swap curve, calculated using a model linking swap rates to sovereign yields, is used to discount liabilities. Under the adverse scenario, the application of Solvency II valuation would lead to a reduction of assets, as the adverse valuation effects in their fixed income portfolio would not be offset by respective movements on the liability side since the swap rate would remain decoupled from sovereign yields. It is important to note that the inclusion of any countercyclical instruments under Solvency II, which are currently under discussion, would alleviate this negative impact.

Equity price losses for individual insurance companies under the adverse scenario are largely related to the volume of such investments, which is rather high for some insurance corporations. The average effect of lapse risk-related losses due to adverse macroeconomic developments turns out to be lower, while the potential losses for insurers related to their property holdings would on average have the weakest impact as a percentage of their assets.

3 APPLYING THE ANALYTICAL FRAMEWORK FOR POLICY ANALYSIS[76]

The forward-looking bank solvency framework is widely used for policy analysis purposes relevant to the ECB. As already alluded to in Chapter 1, the ECB top-down stress testing framework is used in many different contexts. First of all, the analytical framework is used in the regular systemic risk assessment conducted by the ECB as part of its role in supporting financial stability in the euro area. The gist of this analysis is regularly disseminated via the semi-annual *Financial Stability Review* published by the ECB. The framework is also used on a regular basis as part of the macro-prudential analysis provided by the ECB in support of the European Systemic Risk Board (ESRB). Top-down stress testing is moreover used to support the internal financial stability assessment of the ECB, such as identifying pockets of vulnerabilities within the banking sector subject to the materialisation of pertinent systemic risks, and as regular input to the Eurosystem staff macroeconomic projection exercises. As mentioned in Chapter 1, the ECB top-down stress testing tools have also been used in the past to provide various inputs to EU-wide bottom-up stress tests, coordinated under the responsibility of the EBA. Furthermore, such a framework has proved useful in helping to estimate bank recapitalisation needs in the context of the EU/IMF assistance/adjustment programmes introduced in several distressed euro area Member States in recent years. Typically this support has been in the form of using the top-down stress testing framework to cross-check and challenge bottom-up stress test results. Such analytical support will also be valuable to the SSM, once operational.

Against this background, this chapter first provides illustrative examples of results produced for policy-relevant risk assessment purposes. The second part of the chapter describes the use of the framework for cross-checking and challenging bottom-up type stress test results.

3.1 ILLUSTRATIONS OF USES IN REGULAR POLICY ANALYSIS

To illustrate the various breakdowns and dimensions along which the output of the top-down solvency analysis can be presented to inform policy makers, two macroeconomic scenarios (a baseline and an adverse scenario) have been imposed on a sample of large and medium-sized euro area banks. As described in Chapter 2, the adverse scenario incorporates additional stress with regard to macroeconomic developments and also includes shocks to asset prices, leading to mark-to-market valuation losses on trading book assets and higher bank funding costs compared to the baseline.

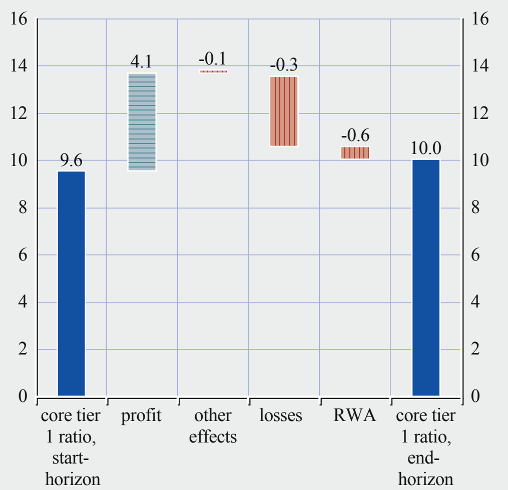
The baseline and adverse scenarios are then processed via the various satellite models, as described in Section 2.2. On this basis, the bank solvency calculations at the level of individual banks are subsequently conducted, following the various steps described in Section 2.3. The output of these calculations can in turn be gauged from various perspectives using different types of data breakdowns and aggregation. Examining the output from a variety of angles (both at the aggregate and disaggregate levels) is crucial to obtain a fully encompassing assessment of the financial stability implications, were the analysed risks to materialise. The following provides various illustrations of the output of the forward-looking solvency analysis and highlights why these specific breakdowns are relevant from a financial stability perspective.

To assess the solvency impact of the baseline and adverse scenarios on the overall EU banking sector, the EU average Core Tier 1 (CT1) capital ratio is a useful metric (displayed in

76 Prepared by Patrizia Baudino, Marco Gross, Christoffer Kok, Miha Leber, Matthias Sydow, Angelos Vouldis and Dawid Żochowski.

Chart 20 Euro area average Core Tier I ratio under the baseline

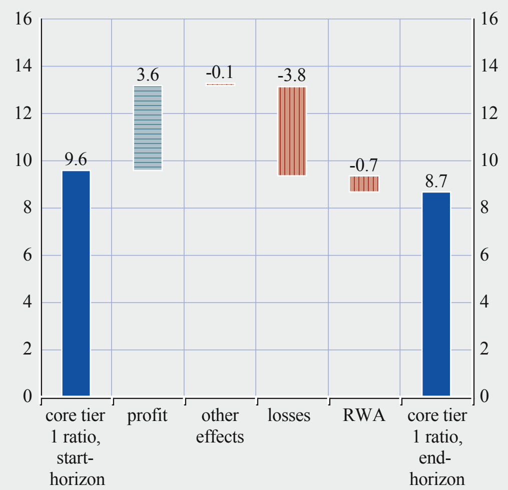
(percentage; average of euro area banks)



Sources: ECB, EBA, banks' reports and ECB calculations.

Chart 21 Euro area average Core Tier1 ratio under the adverse scenario

(percentage; average of euro area banks)



Sources: ECB, EBA, banks' reports and ECB calculations.

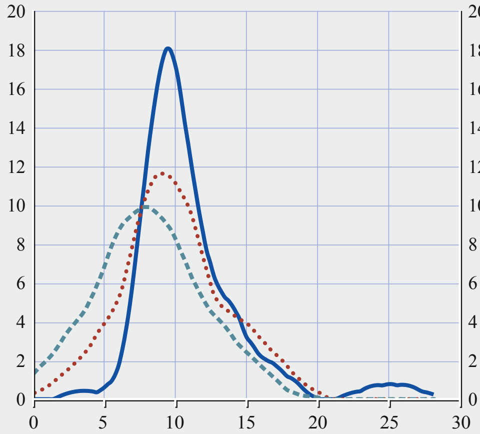
Charts 20 and 21). It provides information about the change in the average CT1 ratio over the forecast horizon both under the baseline and under the adverse scenario. Typically, the end-horizon adverse scenario CT1 ratio is (substantially) lower than the end-horizon baseline CT1 ratio. Indeed, in the example displayed in Charts 20 and 21, there is a 1.3 percentage-point difference in the end-horizon CT1 ratio between the adverse scenario (8.7%) and the baseline (10%).

To gain further insight into the main reasons for changes in bank capitalisation under different scenarios, the changes can be decomposed into their main underlying driving factors, in particular losses, risk-weighted assets and profits. For example, in Chart 20 it is observed that under the baseline, banks' ability to accumulate profits is rather robust and actually exceeds the losses incurred, leading to an overall rise in the average CT1 capital ratio. In contrast, under the adverse scenario (Chart 21) profits are substantially lower than under the baseline and, therefore, are not able to cover the increase in overall losses and risk-weighted assets, leading to a decline in the CT1 capital ratio over the forecast horizon.

In principle, such decompositions of changes in solvency ratios could be even more granular; for example, disentangling what are the main risk components (e.g. credit risk, market risk, etc.) driving bank losses under a given scenario. In general, detailed profit and loss decompositions can play an important role in assessing the channels through which a specific scenario (reflecting particular systemic risks) affect the loss-bearing capacity of the banking sectors, were these risks to materialise.

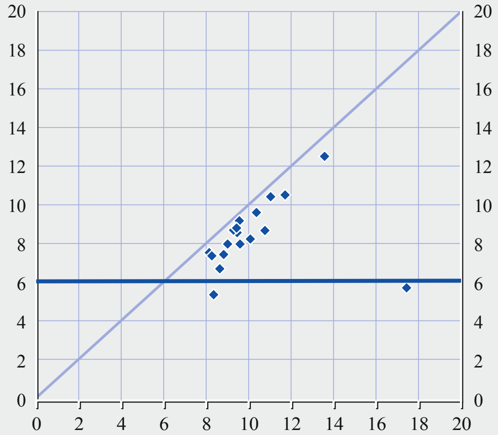
While the impact on solvency positions at the level of the banking sector average is a useful metric from a broad financial stability perspective, being based on individual bank data, the stress testing framework also makes it possible to discern where the pockets of vulnerabilities are. In other words, it allows for identifying which banks are the most fragile, were relevant systemic risks to materialise. For such assessments it is necessary to analyse more deeply the results across the distribution of banks. As an illustration, Chart 22 shows how the CT1 capital ratio distribution of

Chart 22 Probability density distribution of Core Tier I ratios under the baseline and adverse scenarios



Sources: ECB calculations using dummy data.

Chart 23 An illustrative example of individual bank Core TierI ratios under the baseline and adverse scenarios



Source: ECB calculations using dummy data.

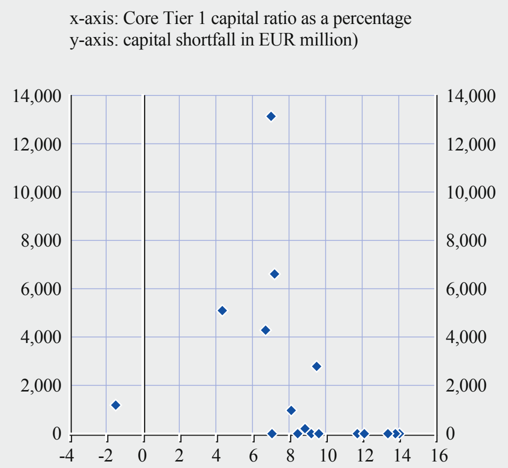
banks in the sample is affected under different scenarios. For example, under the adverse scenario the distribution of banks shifts markedly to the left compared to both the end-sample point and to the baseline. This reflects the fact that the adverse scenario not only results in a lower average CT1 ratio, but that the number of banks falling closer to or below regulatory minima (or any pre-defined threshold ratio) increases. That is, under the adverse scenario, more banks would be at risk of becoming insolvent.

Such distributional effects can also be discerned by comparing (as an illustrative example), for instance, the end-horizon CT1 capital ratio of individual banks under a baseline and an adverse scenario, respectively (see Chart 23).[77] For all the banks depicted in the chart, the end-horizon CT1 ratio is lower under the adverse scenario compared to the baseline. At the same time, it is notable that with two exceptions, all banks remain above a 6% CT1 ratio threshold, even under the adverse scenario. This finding would indicate an overall resilient banking sector based on this particular sample of banks; measured in terms of the first-order solvency implications[78] of the materialisation of the systemic risk underlying the adverse scenario.

As a matter of fact, supervisory stress tests often focus on assessing the potential capital needs of the stressed banks in relation to a pre-defined capital ratio threshold (or a regulatory minimum capital requirement). Such information can obviously also be extracted from a top-down forward-looking solvency analysis. Chart 24 displays (again as an illustrative example, for a sample of EU banks, a plot of country-specific average CT1 capital ratios and the corresponding capital shortfalls (in this case to a 6% CT1 ratio threshold). Such analysis can help detect which banking sectors are particularly vulnerable to specific risks and, were the risks to materialise, what could be the

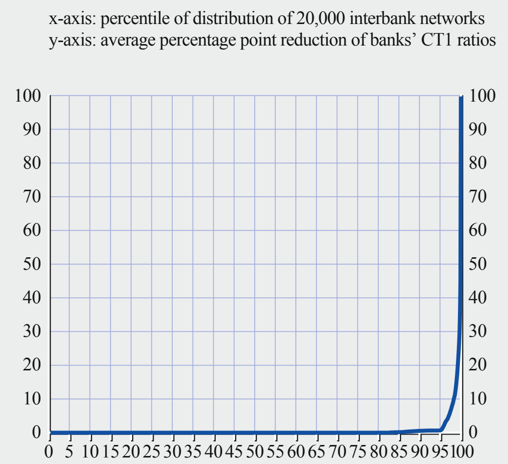
77 Chart 23 includes a smaller number of banks than the sample on which Charts 20-22 are based.
78 That is, excluding contagion risk, which is analysed below.

Chart 24 An illustrative example of country average CT1 ratio and recapitalisation need under the adverse scenarios



Source: ECB calculations using dummy data.

Chart 25 Distribution of changes in banks' CT1 ratios based on simulated networks taking into account interbank contagion



Sources: ECB, EBA, banks' reports and ECB calculations.

potential bank recapitalisation needs. In the illustrative example shown in Chart 24, it is for instance observed that while capital needs are broadly contained in most countries, a number of banking sectors appear vulnerable to the configuration of shocks embedded in the adverse scenario resulting in substantial capital shortfalls.

As described in Section 2.5, the ECB's stress testing framework also integrates an interbank network model of clearing payments, making it possible to study the contagion risk to the overall banking system arising from the first-order solvency shock experienced under a given adverse scenario. Specifically, the interbank structures obtained via the simulated networks approach are applied to measure the distribution of interbank losses transmitted throughout the networks following the assumed default of a group of banks.[79]

A typical finding in the interbank contagion literature is that in most cases, interbank networks remain relatively robust to pure solvency shocks.[80] This finding is, indeed, corroborated when applying the simulated interbank network approach to assess financial contagion following the direct shock to banks' solvency under the adverse scenario. This is illustrated in Chart 25, which shows that in 95% of the 20,000 simulated networks, the adverse scenario does not imply any substantial interbank contagion, measured here as the average system-wide reduction of CT1 ratios following cascading effects of the initial solvency shock under the adverse scenario. Substantial interbank contagion effects could be expected in only 5% of the simulated networks. This underlines the general notion that contagion risk is primarily a "tail risk", but when it materialises it could have detrimental effects on financial stability. For this reason, it is crucial to be alert to potential contagion effects in the tail of the distribution of the simulated interbank networks when assessing pertinent systemic risks.

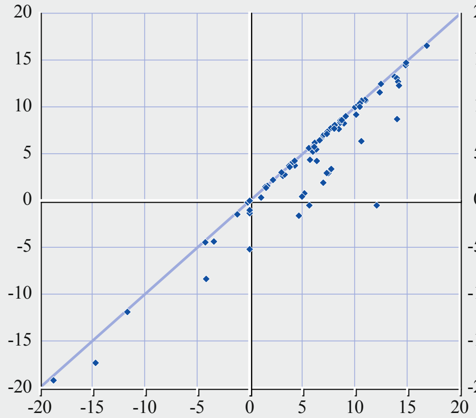
79 In this case, a "default" is defined as a given bank falling below a pre-defined capital ratio threshold.
80 To generate more substantial contagion effects it is typically necessary to also incorporate liquidity shocks, fire sale losses or confidence-based contagion as well.

Focusing on the upper tail of the simulated distribution of networks, Chart 26 displays the CT1 capital ratios of individual banks comparing the end-horizon adverse scenario solvency position (i.e. first-order impact; also displayed in Charts 21 and 23) and the "second-round" solvency position following the interbank contagion arising because some banks default on their interbank payments (assumed to happen when first-round CT1 ratios fall below the 6% threshold). This chart shows that even in the tail of the distribution, many banks are relatively immune to interbank contagion. However, it is also observed that a number of banks could face considerable additional losses as a result of interbank contagion under the adverse scenario (i.e. those banks falling below the 45-degree line).

Chart 26 First round losses under the adverse scenario vs. second round losses taking into account interbank contagion

(99th percentile)

x-axis: end-2014 CT1 capital ratio under adverse scenarios
y-axis: CT1 capital ratio ex-post interbank contagion



Source: ECB, EBA, banks' reports and ECB calculations.

Apart from the obvious focus on bank solvency implications when applying the stress testing framework, the policy analysis using the top-down tool could also be tuned towards much broader macro-prudential topics. Specifically, the framework could be used for calibrating and assessing the implementation of macro-prudential instruments (see Box 5).

Box 5

ASSESSMENT OF MACRO-PRUDENTIAL POLICY TOOLS USING THE STRESS TESTING FRAMEWORK[1]

The advent of new and largely untested macro-prudential powers in the EU, both at the national level and at the supranational level in the context of the SSM, poses considerable analytical challenges for the formulation, calibration and assessment of relevant macro-prudential policy instruments (MPI). Since the Capital Requirements Directive (CRD IV)/Capital Requirements Regulation (CRR) implementing the Basel III standards in the EU and the SSM Regulation foresee the use of MPIs, it will be crucial that the macro-prudential policymaker is in a position to make informed decisions when applying macro-prudential tools. In particular, quantitative knowledge about the impact of the application of an MPI, or a set of those, on the financial sector and the real economy is indispensable to identifying the optimal macro-prudential policy mix. Assessing both the qualitative and quantitative impact of a specific MPI is essential for a policymaker attempting to determine the strength of the policy response. To this end, tools are needed that could (i) mimic the functioning of the propagation channels of macro-prudential policy impulses and (ii) provide information about the relative impact of various MPIs or a combination of those. From an applied perspective, it is crucial that these tools can be adapted to the working structure of the SSM. In particular, the discretion of national supervisors in setting

1 Prepared by Dawid Żochowski with input from Adrien Amzallag, Christoffer Kok and Matthias Sydow.

certain MPIs (e.g. loan-to-value ratio caps, margin and haircut requirements) should be catered for in conjunction with the macro-prudential objectives from the supranational perspective.

With respect to the macro-prudential propagation channels, while some attempts have already been made to model macro-prudential policy in both dynamic stochastic general equilibrium (DSGE) frameworks (see e.g. Kannan et al., 2009; Darracq Pariès et al., 2011; Angelini et al., 2011; Beau et al., 2012; Lambertini et al, 2012; Angeloni and Faia, 2013) and static general equilibrium frameworks (e.g. Goodhart et al., 2012), the importance of different propagation channels and their intertwining needs further exploration.[2] In addition, while some attempts have already been made to include more than one policy instrument in a general equilibrium framework (e.g. Goodhart et al., 2012; and Kawata et al., 2013), most research has so far concentrated on analysing the impact of a single macro-prudential instrument. This makes it challenging to assess the impact of a combination of the instruments in a general equilibrium set-up. Moreover, as macro-prudential policymaking is largely uncharted territory and its theoretical underpinnings are relatively less explored than, say, monetary policy theory, it is prudent to apply a range of tools/models when carrying out impact assessments.

A complementary tool to existing general equilibrium models mentioned above is the top-down stress-testing framework, which could provide valuable information about the relative impact of various MPIs, or a combination of those, on individual banks' capital shortages. While the stress testing framework cannot provide a comprehensive picture of how propagation channels function, such a partial equilibrium set-up can provide a useful input to the overall assessment and calibration of MPIs. Exploring the framework's granular information about banks' balance sheet structure can provide an immediate quantitative assessment of the direct (or 'first order') impact of a given MPI on banks in the cross section. The outcome of such an exercise could subsequently be used as an input to other macro models in order to quantify possible risks arising from macro-feedback effects or contagion. The framework could hence contribute, for instance, to the calibration of the optimal level of countercyclical capital buffers on a country, euro area, or EU level.

To this end, the stress testing framework could act as a platform to calibrate an optimal macro-prudential policy response to a specific shock or a combination of shocks embedded in a scenario, thus providing a policymaker with concrete answers on how to shield the financial system against specific risks, should they materialise. For instance, the optimal level of capital buffer could be estimated by simulating the banking system's response to a hypothetical macroeconomic adverse scenario from the perspective of minimising the second-round feedback effects. Moreover, owing to the granular information on banks' exposures, sectoral capital requirements and/or risk weights could be calibrated in order to find an optimal macro-prudential policy response to a specific sectoral shock, such as a negative house price shock or an increase in probabilities of default of a specific corporate sector. Concerning liquidity-based MPIs, the framework could in principle also provide information on an optimal level for the liquidity coverage and the net stable funding ratio, for example given an adverse scenario involving pervasively tight liquidity conditions in funding markets. Furthermore, different levels of loan-to-value and loan-to-income ratios, the setting of which will remain in the domain of local authorities, could be reflected in the differentiation of LGD and PD parameters within the framework, respectively.

This notwithstanding, using the stress testing framework for macro-prudential purposes poses some analytical challenges. First, while an optimal level of capital buffer could be calibrated

2 For a review of the recent literature, see also ECB *Financial Stability Review*, May 2013, Special Feature A entitled "Exploring the nexus between macro-prudential and monetary policies".

using the framework, no clear answer would be provided regarding its allocation across various capital-based MPIs, such as counter-cyclical capital buffers, systemic risk buffers or the SIFIs capital surcharge. Second, identifying the optimal on/off path for the capital surcharges or, more broadly, the optimal application of any MPI in a dynamic manner requires the definition of a clear policymaker objective function.[3] Furthermore, while macro-prudential tools based on capital surcharges, changes in risk weights and counterparty limits should be relatively easy to apply in such a framework, adequately reflecting the impact of liquidity-based MPIs is less straightforward.

3 This objective function remains theoretically almost unexplored but, as with monetary policy responses, is required to provide (i) a comparative measure against which MPIs' impacts can be compared and (ii) a common reference to facilitate the decision-making process of policymakers.

3.2 USING TOP-DOWN STRESS TESTS TO REVIEW BOTTOM-UP STRESS TEST RESULTS

Accompanying a bottom-up stress test with a top-down review has become common practice in recent years. ECB staff have been involved in various efforts to cross-check bottom-up stress tests performed either by i) individual banks (e.g. in the case of the EBA EU-wide stress testing exercise), ii) independent consultancy companies (e.g. for the banking sector of countries under EU/IMF programmes) or iii) national supervisors. This subsection describes the use of the top-down stress testing infrastructure for bottom-up cross-checks, based on such recent cases.

The idea behind a top-down review of bottom-up stress test results is that the former, being carried out at a centralised level without involving the banks being stressed, can provide a more impartial (if less precise[81]) assessment of the solvency needs of individual banks. From a supervisory point of view, bottom-up stress test results produced by the banks will inevitably have to be viewed through a critical lens owing to the misalignment of incentives (i.e. the banks will have a natural tendency to stress test results that imply no subsequent management actions). The top-down review can help make the supervisory assessment of bottom-up results more objective.

Depending on data availability, the top-down cross-check of bottom-up results can be focused either on individual drivers of a solvency analysis or on the overall capital shortfall given a pre-defined capital ratio threshold. For banks with very complex business models (e.g. a bank with large trading activities including derivative positions and hedging) it can be difficult to provide a top-down estimate of the overall capital shortfall under a given stress scenario. In such cases, some of the required data inputs would need to be so granular that the process would be *de facto* unfeasible. It is therefore often more meaningful to review individual capital shortfall drivers, such as loan losses or net interest income, instead of the overall capital shortfall outcome.

In general, data needs exceed those for the standard supervisory monitoring of banks. The modelling of bank-specific balance sheet and P&L items in a stress testing exercise requires very granular inputs. This varies, however, with the type of stress test conducted. Data needs can usually be classified along the following dimensions: time, counterpart, country of exposure and maturity. For instance, in the case of a loan for house purchase, a breakdown by maturity, counterpart, and country of exposure, as well information about the initial interest rate fixation period (e.g. fixed vs. floating lending rates), would be needed. In addition, it is important to collect a larger

81 Owing to the fact that typically less granular bank level data are available to the top-down stress tester.

history for those variables that will be linked to macro-financial shock scenarios via satellite models (e.g. bank-specific time series for PDs, LGDs, NPL, loan and deposit volumes, lending and deposit rates). The following non-exhaustive list provides a couple of examples of other relevant data:

- Breakdown of impaired loans and advances and debt securities by counterpart and country;
- Information on interest rates for outstanding stocks of various balance sheet items;
- Country breakdowns for loan exposures and deposits;
- Asset quality indicators, such as PD and LGD, by counterpart and country of exposure;
- Breakdown of profitability indicators such as net interest income or net fee and commission income into further sub-components (e.g. interest income by business line, clearing and settlement fees, payment services);
- Unconsolidated information for the modelling of foreign subsidiaries;
- Existing stock of provisions (ideally broken down by portfolio segment);
- Existing stock of capital (broken down by instrument categories; e.g. Core Tier 1, Tier 1 and Tier 2 capital);
- Breakdown of RWAs on a consolidated basis and solo basis (for domestic operations and foreign subsidiaries).

In terms of parties involved, it is useful to include all relevant stakeholders from the very beginning of a stress-testing exercise that includes both bottom-up and top-down components. This allows the needs of both processes to be streamlined. Typically, the bottom-up stress test involves either i) individual banks, which receive instructions from their supervisory agency, ii) an independent consultancy firm, tasked with the job of running a bottom-up stress test using bank-internal data, or iii) a national supervisor. The top-down stress test is either i) run by the supervisor (national or supranational), ii) a non-supervisory international organisation (such as the EC, ECB and IMF) or iii) an independent consultancy firm.

In terms of timing, the top-down stress test would usually be performed in parallel to the bottom-up stress test, so that results can be compared at the end of the process.

Concerning the organisation of the process, the exercise may be coordinated by a task force or steering committee, which can comprise international experts from ESA(s), EU organisations and the IMF (e.g. in the case of EU/IMF programme evaluations). Usually, at the beginning of the process, a committing timeline with several milestones is made public. It is therefore crucial to have a good project plan allowing for sufficient time buffers in case of unforeseen problems, mostly arising due to data quality issues. The following key milestones need to be considered:

1. Definition of the general perimeter of the exercise and of the methodological guidance;
2. Definition of data templates and data collection;

3. Interim bottom-up and top-down stress test results;

4. Comparison of interim bottom-up and top-down results;

5. Revision of bottom-up results and production of final results;

6. Endorsement of final results by all relevant stakeholders;

7. Publication of results.

The process of cross-checking bottom-up and top-down results generally begins after the finalisation of the interim bottom-up results, which are usually shared with all relevant parties in the form of granular data outputs along with a report describing the relevant methodological assumptions and models.

The cross-check involves a qualitative and quantitative review of the various stress test components. For each bank in the sample, as well as the aggregate system, the following broad steps should be covered:

1. Clarification of starting point data discrepancies between bottom-up and top-down data, e.g. due to the aggregation/consolidation of bottom-up information;

2. Outlier detection for bottom-up starting point data and baseline/adverse forecasts, via statistical analyses using historical data or banking system aggregates as a reference;

3. Comparison of satellite model-driven bottom-up and top-down results taking into account top-down model error bounds;

4. Comparison of non-model based assumptions (e.g. staff expenses, treatment of operational risk, fee and commission income);

5. Plausibility checks of bank-specific business plans and banking system results.

Step one from the above list is usually the most time consuming part of a bottom-up cross-check and requires, therefore, sufficient time buffers in the planning. While steps two to four usually examine individual stress test drivers, e.g. loan losses, step five goes a bit further by combining all stress test drivers into a broad picture of an individual bank and the national banking systems. This allows for a plausibility check of bank-specific business plans, provided along with the baseline projections. Plausibility checks should cover balance sheet changes in terms of both volumes and related prices.

Box 6

LIQUIDITY / FUNDING RISK ASSESSMENT[1]

Liquidity risk – some general considerations

The fundamental role of banks in the maturity transformation of short-term deposits into long-term (illiquid) loans makes banks inherently vulnerable to liquidity risk. In general, one can distinguish between two types of liquidity risk: "funding liquidity" (i.e. the risk that a bank will be unable to rollover maturing funding) and "market liquidity" (i.e. the risk an asset cannot be sold or used as collateral due to insufficient liquidity in the market). While reflecting distinct bank activities, both sources of risks can be strongly interlinked and may feed onto each other, in particular during periods of stress.[2] Furthermore, notwithstanding the generally close link between a bank's solvency position and its ability to obtain market funding, owing to the systemic nature of financial crises even a sound solvency position does not guarantee a bank's access to market funding. Moreover, the sale of assets that are liquid in normal times can be costly or impossible in stress periods. The collateral value of such assets is reduced accordingly.

The increasing reliance of banks on wholesale and interbank short-term funding over the last two decades considerably increased banks' liquidity risks.[3] However, over the same period many banks neglected to enhance their liquidity risk management and buffers. The reversal of the beneficial pre-crisis funding market conditions, beginning with higher costs, evolved quickly into the closure of some segments of the wholesale funding market, in particular for unsecured funding. The banks' liquidity situation was aggravated further by unexpected usage of liquidity lines granted to their customers and difficulties in selling assets, formerly perceived as liquid. To prevent systemic consequences, central banks had to intervene as lender of last resort by providing ample liquidity – also in major foreign currencies. These events highlighted that the regular prudential monitoring and assessment of liquidity risks are essential to ensure a resilient banking sector. At the same time, it should be recognised that liquidity crises occur at very low frequency, but are sudden and high impact events that leave banks very little time to react. Moreover, each liquidity crisis is different in terms of transmission channels and affected banks, so that the informative value of single measures of banks' resilience to liquidity shocks is limited.

Regulatory principles, guidelines and minimum requirements

The Basel Committee on Banking Supervision (BCBS) reacted to the deficiencies of banks' liquidity management and supervisors' assessments of liquidity risks by formulating 17 qualitative principles for sound liquidity risk management and supervision (BCBS 2008). These principles comprise the obligation for banks to establish a liquidity risk tolerance; to allocate liquidity costs, benefits and risks to all significant business activities; and to identify and measure the full range of liquidity risks, including contingent liquidity risks. Moreover, banks are obliged to develop a robust and operational contingency funding plan, to maintain an adequate level of liquidity, including through a cushion of unencumbered (i.e. not yet used as collateral), high quality liquid assets, as well as to conduct liquidity stress tests on a regular basis.

1 Prepared by Maik Zimmermann with input from Maciej Grodzicki, Grzegorz Hałaj and Christoffer Kok.
2 See, for example, Brunnermeier and Pedersen (2009).
3 See also ECB (2012), "Changes in bank financing patterns", April.

In December 2010, the BCBS disclosed a framework for liquidity risk measurement, standards and monitoring as part of the new Basel III regulation (BCBS 2010). The most important aspect of this framework is the definition of two quantitative minimum liquidity ratios, the liquidity coverage ratio (LCR) and the net stable funding ratio (NSFR). The LCR requires banks to hold sufficient high quality liquid assets (cash, government bonds and other high rated liquid securities) to meet a severe cash outflow for at least 30 days, with banks being allowed to offset up to 75% of this outflow by an assumed inflow of funds that mature within the next 30 days.[4] After the BCBS has revised the computation of the LCR, it will come into effect as planned on 1 January 2015, but under a gradual phase-in arrangement to reflect the difficulties that banks in countries under stress will have complying with the LCR requirement. The minimum LCR will increase from 60% in 2015 to 100% in 2019 (BCBS 2013).

The NSFR has been created to address structural liquidity mismatches. The calculated available amount of stable funding[5] is required to at least match the required amount of stable funding over a one-year horizon in an environment of prolonged funding difficulties. Thus, the NSFR promotes funding via deposits or medium- to long-term securities over short-term wholesale funding and incentivises banks to hold a sufficient stock of short-term or high quality securities. Barring any revisions to the timetable, the NSFR will move to a minimum standard by 1 January 2018.[6]

Given that the LCR and the NSFR are, on their own, insufficient to measure all dimensions of a bank's liquidity profile, the BCBS has also developed a set of monitoring tools to further strengthen and promote global consistency in liquidity risk supervision. These tools comprise the contractual maturity mismatch profile, an analysis of funding concentrations, the calculation of the stock of available high quality unencumbered assets, and the computation of the LCR for significant currencies, as well as market-related monitoring tools.

Bank liquidity stress testing and top-down liquidity risk assessments

BCBS (2008) requires banks to conduct liquidity stress tests on a regular basis for a variety of short-term and protracted institution-specific (i.e. idiosyncratic) and market-wide stress scenarios (both individually and in combination) to identify sources of potential liquidity strain, and to ensure that current exposures remain in accordance with a bank's established liquidity risk tolerance. Depending on the outcome of the liquidity stress tests, banks should adjust their liquidity risk management strategies, policies and positions, as well as develop effective contingency plans.[7]

Supervisors and central banks conduct top-down liquidity risk assessments in addition to the bottom-up stress tests run by banks. The purpose of top-down liquidity risk assessments is to

4 The inflow of funds may not be calculated at face value, but by applying different weightings (e.g. 50% for amounts to be received from retail or non-financial wholesale counterparties) to take into account that a going-concern bank would not completely cease new lending – even in a severe funding stress scenario.
5 "Stable funding" is calculated by weighting the different funding sources of the bank according to their run-off potential. In other words, funding perceived as less susceptible to sudden withdrawals receives a higher overall weight.
6 The European Banking Authority discloses the progress of a large sample of European banks to comply with the requirements of the Basel III framework, including the LCR and the NSFR, on a semi-annual basis (e.g. EBA 2013).
7 The Committee of European Banking Supervisors disclosed guidelines on liquidity buffers and survival periods in December 2009 (CEBS 2009). In these guidelines, the CEBS required that banks apply idiosyncratic, market-wide and combined stress scenarios. While idiosyncratic stress should assume the impossibility of rolling over unsecured wholesale funding in combination with some outflows of retail deposits, market-wide stress scenarios should assume a decline in the liquidity value of some assets and deterioration in funding market conditions.

reveal the counter-balancing capacity of banks to remain liquid and their specific limit in case of reverse stress tests[8] to allow for comparisons with peers by illustrating the relative performance of banks under the chosen scenario(s), as well as to provide a link between the joint resistance to liquidity and solvency risks (if included in the model).[9]

Conditional on full data availability, top-down liquidity risk assessments could be run based on a detailed breakdown of banks' contractual cash flows in different maturity buckets and behavioural data[10] based on banks' funding plans. In the absence of behavioural data, expert judgement can help to calibrate adequate stress assumptions. The calibrated scenarios would then incorporate roll-over assumptions for contractual cash-outflows and cash-inflows, the latter taking into account the banks' objective of maintaining its franchise value by conducting new business even under funding stress. Such an analysis allows for an intuitive view of each banks' liquidity risk-bearing capacity in the form of the cumulated counterbalancing capacity at the end of each maturity bucket. Reverse stress tests could additionally be conducted.

Under the Basel II regulatory framework, the assessment of banks' liquidity risk was assigned to Pillar 2, i.e. left to the discretion of the respective national supervisor; data on banks' contractual cash flows are therefore only available to some supervisors and central banks (which will improve, however, once Basel III is implemented).[11] For that reason, top-down liquidity risk assessment exercises are usually conducted based on implied cash flows. These are calculated by taking a simple balance sheet breakdown, sometimes based on publicly available data only, and assuming appropriate run-off rates for the different funding sources, roll-over rates for assets, haircuts for the stock of high liquid assets to assume they are sold at fire sale prices, and drawings of banks' contingent liabilities. Information on asset encumbrance cannot often be accurately matched with cash flow and balance sheet data, so the counterbalancing capacity needs to be prudently estimated from the balance sheets. In substance, the scenarios for top-down liquidity risk assessments are very similar to those of bottom-up stress tests and include idiosyncratic, market-wide and combined funding shocks.[12] Also, the top-down liquidity risk assessments could focus either on short-term, bank-run-like set-ups, such as the scenario used for the calculation of the LCR, or have a medium- to long-term perspective by taking into account maturity mismatches like the NSFR.

Finally, liquidity and solvency risks can be linked in a macro stress test framework e.g. via higher funding costs, the increase of collateral needs for secured funding, the closure of funding markets based on a bank's solvency position, or the default of a bank's major liquidity providers. As a bank's costs for (wholesale) funding are closely related to its ratings, for which its solvency position is a major input variable, a deterioration of the bank's initial solvency position increases its interest expenses and reduces *ceteris paribus* its capital ratios at the end of the stress test

8 Reverse stress tests seek to identify the maximum stress resistance of banks and the banking system by increasing the risk factors (such as haircuts and run-off rates) until a predefined threshold (e.g. positive counter-balancing capacity) is reached.
9 See also Schmieder et al. (2012).
10 That is, information about banks' future investment and refinancing actions.
11 The CRD IV / CRR, which translate Basel III into EU law, require European banks according to Articles 415 and 416 to report to their respective supervisor a detailed breakdown of their assets and liabilities into five maturity buckets (within 3 months, between 3 and 6 months, between 6 and 9 months, between 9 and 12 months and after 12 months) at least on a quarterly basis.
12 For example, the Swedish central bank (Riksbank) requires Swedish banks to regularly calculate and disclose a short-term liquidity measure (similar to the LCR, but calibrated on a 3-month stressed scenario and providing a survival period instead of a ratio) as well as a structural liquidity measure (like the NSFR calculated over a one-year horizon and providing a ratio, but based on slightly different assumptions).

horizon.[13] In the aforementioned model framework, the liquidity element (i.e. higher funding costs) hampers a bank's ability to pass a solvency test, while higher collateral needs for secured funding, the closure of funding markets or the default of a bank's major liquidity providers hampers a bank's ability to maintain a certain degree of liquidity.

13 The decline of the capital ratios at the end of the stress test horizon depends on the bank's ability to pass through the higher funding costs to its customers, i.e. to generate higher interest income.

4 CONCLUSION [82]

Macro stress testing has become an increasingly popular tool for assessing the resilience of financial institutions to adverse macro-financial developments. The recent financial crisis and the euro area sovereign debt crisis, which exposed the financial sector to unprecedented adverse shocks, reinforced this trend.

Macro stress tests come in different configurations. A broad distinction can be made between bottom-up stress tests carried out at the level of the banks, and top-down stress tests carried out at a centralised level without involving the banks being stressed. Both approaches have their advantages and disadvantages but are largely complementary.

This Occasional Paper has presented the top-down stress testing framework developed and employed at the ECB. This forward-looking solvency analysis assessment tool has many uses, including input into the regular financial stability risk analysis of the ECB, into the Eurosystem staff macroeconomic projection exercises, and for cross-checking bottom-up stress test results. Going forward, the analytical framework presented here will also provide a useful tool for the supervisory stress testing activities of the SSM. Furthermore, there is also scope for using the top-down stress testing framework for the evaluation of specific macro-prudential policy instruments.

Despite the substantial analytical advances in stress testing techniques made in recent years by the ECB and other institutions, several challenges remain. Fundamentally, stress testing is more an art than a science. This also relates to the elusive nature of systemic risk that macro stress testing is supposed to capture. Especially, current macro stress testing tools have difficulties capturing the non-linear character of systemic events and the various feedback mechanisms between banks and between the banking sector and the real economy that such events usually entail. Whereas some stress testing frameworks, including the one presented here, have already made steps towards overcoming some of these analytical challenges, further efforts are clearly needed in coming years to improve the overall reliability and accuracy of stress test exercises.

82 Prepared by Jérôme Henry and Christoffer Kok.

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