EUROPEAN CENTRAL BANK

EUROSYSTEM

STAMP€:

Stress-Test Analytics for Macroprudential Purposes in the euro area

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Contents

Foreword

By Vítor Constâncio, Vice-President of the ECB

Systemic risk measurement

Financial sector stress tests have proved to be an important tool for assessing the robustness of the financial system and gauging risks arising at system-wide level from a macroprudential perspective. This European Central Bank (ECB) publication – Stress Test Analytics for Macroprudential Purposes in the euro area (STAMP€) – offers a suite of analytical tools for those interested in stress-testing frameworks and has been developed by ECB staff over the past few years. In 2013, the ECB published an occasional paper describing the framework and its various modules[1] for conducting stress tests. These had been used since 2009 to support the EU-wide stress test by the Committee of European Banking Supervisors and later by the European Banking Authority (EBA). Since 2013, new modules and tools have been developed. These tools go well beyond the requirements of the traditional solvency stress tests applied to banks. They include a broader set of institutions than just banks, an analysis of the financial cycle as well as an assessment of systemic risk levels associated with the economic and financial shocks considered in adverse scenarios.

The financial crisis and its aftermath led to a greater use of stress tests and to the establishment of macroprudential policy as a new policy area, with the objective being to identify and limit systemic risk. In the ECB Financial Stability Review, systemic risk is defined as "the risk that financial instability significantly impairs the provision of necessary financial products and services by the financial system to a point where economic growth and welfare may be materially affected".[2] At the heart of this definition is the notion that the materialisation of systemic risk imposes significant costs on the real economy.

The literature has identified three broad sources of systemic risk: (i) macroeconomic shocks that are significant enough to cause distress in the financial system, (ii) the unwinding of imbalances in the financial system generated by excessive leverage, and (iii) contagion risk, created by increasing interconnectedness and herd behaviour.

Several indicators to measure systemic risk have been proposed since 2008. The first type of indicators has a "micro-level" dimension, i.e. it calculates the contribution of significant institutions individually to systemic risk. The Marginal Expected

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[1] Henry, J. and C. Kok Eds. (2013), "A macro stress testing framework for assessing systemic risk in the banking sector", *ECB Occasional Paper No 152*.

[2] See also ECB (2009), *Financial Stability Review*, Special Feature B for a discussion on the concept of systemic risk.

Shortfall (MES), Conditional Value at Risk (CoVar), CoRisk or Conditional Tail Risk (CRT), for example, fall into this category.[3] Taken in isolation, they do not help to predict future levels of systemic risk, as they tend to use contemporaneous market prices and do not consider the system as a whole.

Composite indicators such as the ECB's Composite Indicator of Systemic Stress (CISS)[4] represent a second type of measure. It comprises five aggregate market segments accounted for by a range of variables and time-varying rank correlations between them. Another example is CATFIN, a value-at-risk and expected shortfall measure at system-wide level, calculated with non-normal distributions with fat tails, showing the predictive capacity of financial volatility regarding real economic downturns.[5]

A third type of approach complements these efforts and relates to the concept of the financial cycle, in contrast to that of the economic or business cycle. In fact, a country's positioning in the financial cycle – with respect to a historical benchmark – can be seen as a systemic risk indicator and be used to predict overall levels of risk in the system. In that context, a first step was taken in a recent ECB working paper[6] building on and extending work done at the Bank for International Settlements (BIS) on the financial cycle.[7] It shows how credit and asset prices share cyclical similarities, captured in a synthetic financial cycle index that outperforms credit-to-GDP gap measures in predicting systemic banking crises, on a horizon of up to three years.

Another complementary approach for assessing overall levels of systemic risk in the system could result from adding a macroprudential perspective to the analytical tools used in traditional bank solvency stress tests. In 2015, I elaborated on this whole concept, which seems to me a natural development.[8] An initial application of this approach in the wake of last year's EBA stress tests was described in the ECB Macroprudential Bulletin of November 2016.[9]

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3 For an overview, see Bisias, D., M. Flood, A. W. Lo and S. Valavanis (2012), *"A Survey of Systemic Risk Analytics"*, *Office of Financial Research Working Paper No 1*, January.

4 Holló, D., M. Kremer and M. Lo Duca (2012), *"A composite indicator of systemic stress in the financial system"*, *ECB Working Paper No 1426*, March.

5 Allen, L., T.G. Bali and Y. Tang (2012), *"Does systemic risk in the financial sector predict future economic development?", The Review of Financial Studies, Vol. 25, No 10*, October, pp. 3000-3036.

6 Hiebert, P., T.A. Peltonen and Y. Schüler (2016), *"Characterising the financial cycle: a multivariate and time-varying approach"*, *ECB Working Paper No 1846,* September, and an updated presentation at the ECB-IMF Conference on Macroprudential Policy Frankfurt, 26-27 April 2016.

7 Borio, C., M. Drehmann and K. Tsatsaronis (2012), *"Characterising the financial cycle: don't lose sight of the medium term!"*, *BIS Working Paper No 380*, June.

8 The role of stress testing in supervision and macroprudential policy, keynote address by Vítor Constâncio, Vice-President of the ECB, at the London School of Economics Conference on "Stress Testing and Macroprudential Regulation: a Trans-Atlantic Assessment", London 29 October 2015. Also available from VoxEU as a CEPR Press e-book edited by Ronald W. Anderson (2016), "Stress Testing and Macroprudential Regulation: a Transatlantic Assessment".

9 "Macroprudential effects of systemic bank stress", Chapter 1, ECB (2016) *Macroprudential Bulletin, Issue 2*, October.

Limitations of traditional stress test methodologies

One important lesson of the financial crisis was that the need to go beyond the micro-supervision goal of ensuring the robustness of individual financial institutions, particularly banks, was recognised. We learnt that the system can collapse even if, individually, institution by institution both solvency and liquidity positions seem quite safe. The degree of interconnectedness within the system, contagion through herd behaviour and the sudden vanishing of inside liquidity within the financial system, are realities that justify system-wide surveillance as well as the new macroprudential policy area. The ultimate objective of macroprudential policy is to prevent and mitigate systemic risk, which includes strengthening the financial system and smoothening the financial cycle, in order to preserve the effective provision of financial services to the real economy.[10]

In the aftermath of the crisis, microprudential solvency stress tests were promptly used to assess the capital needs of individual banks. However, this tool soon showed significant limitations in the face of macroprudential policy concerns.

Among these limitations is the static balance-sheet approach, which is not well suited to stress-testing exercises that run for a horizon of three years. This may render the tests unduly conservative if the macro scenario is too severe. No bank reaction is considered, whereas in practice banks react to adverse conditions by deleveraging, making straight capital increases or working out non-performing loans. Each action of this kind would in turn have different macrofinancial consequences that would affect the economic environment.

Another weak feature is that the adverse scenario shocks are treated as exogenous to the financial sector and that feedback loops between credit institutions and the economy as a whole are ignored. Macroprudential stress tests should provide, in association with the adverse scenario, indicators to gauge the potential level of systemic risk related to each country's position in the financial cycle. Higher capital requirements imposed on individual institutions may either not be enough to safeguard financial stability or, in different circumstances, may aggravate the overall financial stability conditions, requiring easing or release of macroprudential measures.

In the same vein, traditional stress tests do not include any interaction between banks and other specific sectors of the economy, whether households and corporates or other non-bank financial institutions, particularly asset managers and investment funds of all types.

Furthermore, no complete liquidity assessment is integrated in the microprudential solvency stress tests. This omission should be addressed, given the strong two-way interaction between liquidity and solvency strains brought to the fore by the global financial crisis.

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10 See Vítor Constâncio (2016), "Principles of macroprudential policy", speech at the ECB-IMF Conference on Macroprudential Policy, Frankfurt, 26-27 April 2016.

These weaknesses can only be tackled in a true top-down macroprudential stress test framework, centrally conducted.

Macroprudential stress tests

STAMP€ is a relevant step towards providing an analytical framework for macroprudential stress tests. Beyond the macroprudential dimension of stress testing, the STAMP€ e-book presents top-down models that support the EU-wide stress-testing exercises – primarily microprudential solvency exercises – that are part of the overall framework (see Chapters 1 to 8). Regarding the macroprudential extension of stress testing, and corresponding to the shortcomings I mentioned before, the approach comprises five main domains to which analytical work presented in this e-book contributes.

First: the **dynamic dimension**. Macroprudential stress tests should encompass a dynamic approach that takes into account banks' responses to the scenario. The tests need to account for realistic features of systemic stress, in particular banks' behavioural reaction to the stress, as opposed to the static balance-sheet approach. Banks could react by deleveraging, raising capital or working out non-performing loans, for example. Typically, their reactions in the crisis caused the initial stress to escalate. This could be achieved by introducing a dynamic balance sheet that allows banks to re-optimise their portfolio according to the risk-return optimisation criterion (see Chapters 2 and 9), thereby departing from the traditional static approach.

Second: the **interaction with the real economy**. Macroprudential stress tests should take into account the two-way interaction between banks and the real economy as well as the related macro-feedback effects generated by banks' balance sheet adjustments. To this end, a DSGE model calibrated for individual countries (see Chapter 10) and a Global Vector Autoregression (GVAR) model (Chapter 11) are being used, allowing for an assessment of the cross-border effects of deleveraging. Results tend to confirm the common wisdom that, in response to a negative shock to the leverage, banks tend to shed assets instead of raising capital, while keeping the leverage constant.

Third: the **interconnections between financial institutions**. Macroprudential modelling approaches need to account for interconnectedness among institutions and related contagion effects that can amplify the initial stress system-wide. Here, knock-on effects related to financial contagion and resulting from dynamic interactions between the financial economic agents are considered. Contagion via the interbank channel, already featuring in the ECB top-down stress-testing framework, is being refined (see Chapter 12). Stress-testing methodologies also need to include interaction with the financial sector, including the shadow banking sector, which continues to grow at a steady pace. These methodologies should help to reveal vulnerabilities in this sector and assess the potential for spillovers to the rest of the financial sector, most prominently due to fire sales. Agent-based models, allowing for endogenous asset price determination, can be used to account for such interactions (see Chapter 16).

Fourth: the integration of **system-wide liquidity assessment** in the stress-testing framework. There are two dimensions to this issue: one related with the interconnection between liquidity and solvency at the level of individual institutions; and the other, reflecting the consequences for overall liquidity associated with the interconnectedness and network effects within the financial system as a whole (see Chapter 14).

Fifth and finally, macroprudential stress-testing methodologies need to account for **interaction with non-financial sectors** that are relevant for banks' risk management. A module presented in STAMP€ integrates the household sector of the economy in the stress-testing framework in order to properly account for vulnerabilities that may emerge from it (see Chapter 15). Using the data from the ECB Household Finance and Consumption Survey, a framework for stress testing balance sheets of households allows for the computing of the probability of default and loss given default for mortgage exposures directly at household sector level and links them to macroeconomic stress scenarios.

Such enhancements to the ECB top-down stress-testing framework also provide a tool for the **impact assessment of macroprudential policy instruments**. These policy instruments are designed and calibrated to address systemic risks. As such, assessing macroprudential measures in a consistent and holistic manner requires taking into account interactions within the banking sector as well as interactions with the financial and non-financial sectors and the real economy.

This publication represents the first step in a long journey, as reflected by the chapter on future extensions of the framework (see Chapter 16). It is a journey which goes well beyond banking, aiming at setting up a comprehensive stress-testing capacity for the financial sector as a whole. This ambitious endeavour requires the use of many different methods and models, from macroeconomic models to Bayesian Vector Autoregression (BVAR), to network contagion analysis or agent-based models. It requires putting together several analytical capabilities and the fostering of collaboration between many researchers and experts in different fields. To meet its responsibility for financial stability, the ECB is committed to continuing its work on developing an integrated framework appropriate to the assessment of the macroprudential policy stance. By publishing this e-book on the work in progress, we hope to engage the community of stakeholders in macroprudential issues, from academics to researchers in official institutions, in a fruitful dialogue and thereby improve the existing methodologies.

Chapter 1 Editors' introduction

By Stéphane Dees, Jérôme Henry and Reiner Martin

The material reported in this book – focusing on macroprudential stress-testing tools – would likely not have come to life without the financial crisis that started in 2007. Stress testing from a system-wide perspective, i.e. beyond bank-specific risk analysis, let alone for macroprudential purposes, was not clearly envisaged before the crisis. In ancient Greece, the word "crisis" meant a decisive moment. It was used by Hippocrates, among others, to refer to the moment where in the face of a critical situation decision-makers, and physicians at the time, have to take key steps. Jean Monnet, an early proponent of European unity, combined the ancient and current meaning of "crisis" when stating that « Les hommes n'acceptent le changement que dans la nécessité, et ils ne voient la nécessité que dans la crise » ("People only accept change out of necessity and see necessity only in times of crisis").

The financial crisis triggered far-reaching structural changes, especially in Europe, with institutional as well as operational implications. Decisive steps taken in Europe following the crisis include the banking union in its various dimensions – not least the creation of the Single Supervisory Mechanism (SSM) and the corresponding joint approach to microprudential and macroprudential policies. This dual approach is reflected inter alia on the operational side in the use of system-wide stress-testing, calling for specific toolkits to be developed that can bring together the macroprudential and microprudential dimensions, from both a data and an analytical perspective.

ECB staff became involved in stress test-related tasks at a relatively early stage, in the late 2000s, contributing to the design of scenarios for the first EU-wide stress test under the Committee of European Banking Supervisors (CEBS), and afterwards for similar exercises carried out by the European Banking Authority (EBA). With the creation of the ESRB in 2011, and its macroprudential focus, specific additional attention had to be paid to the potential impact of systemic risk on the financial sector and beyond. With that aim in mind, an impact assessment toolkit was required that would adequately combine the micro dimension of bank-level data and the macro aggregate perspective. The ECB staff approach to this is documented in an ECB Occasional Paper, namely Henry and Kok (2013). These tools were employed for work on crisis countries in the euro area as well as in the context of the ECB comprehensive assessment in 2014, prior to the inception of the SSM.

With the creation of the SSM, the macroprudential policy function now given to the ECB required a further enhancement of the toolkit, in a number of ways. Given its system-wide and economy-wide focus, macroprudential analysis has to take much more into account than solely the direct impact of shocks to individual entities and their magnitude in aggregated terms – thereby going well beyond standard supervisory stress-tests. In particular there is a need to include in the analysis the reaction of banks to stress, as well as spillovers both within the banking sector and from banks to other financial sectors. The toolkit should also help quantify the impact of specific policy measures. Furthermore, a proper and relevant macroprudential assessment requires the analysis of interactions between the financial system and the real economy, supported by various macro-financial models.

Accordingly the Stress-Test Analytics for Macroprudential Purposes for the euro area (STAMP€), which is the stress-testing framework put together by ECB staff, not only features top-down models for microprudential purposes, but also includes modules that were specifically developed for macroprudential analyses. First results were published in the ECB Macroprudential Bulletin (see ECB 2016), following up on the EBA/SSM stress test completed earlier in the same year.

A description of the overall framework of STAMP€ is given in Chapter 2. Updating and extending Henry and Kok (2013), the chapter provides an overview of the top-down stress testing framework now employed at the ECB. New elements mostly concern a deeper analysis of feedback effects, including dynamic balance-sheet analyses, second-round effects involving the macroeconomic environment, and contagion impacts involving the banking sectors and other sectors. This chapter aims overall at operationalising the "vision" sketched out by Constâncio (2015) on the macroprudential dimension of stress-testing exercises.

As an illustration of what this extended framework can deliver, Chapter 3 elaborates on a macroprudential extension of the recently conducted EU-wide bank stress test. The purpose of this STAMP€ macroprudential application is to quantify the impact of macroeconomic and systemic effects that were not analysed in the microprudential stress-testing exercise but that are nonetheless extremely relevant and potentially sizeable.

After these overview chapters, the remainder of the book is devoted to giving further details on the various elements of STAMP€. It is structured in three different parts: the satellite models, the estimation of the macroeconomic feedback and the estimation of the contagion effects. A final part presents further extensions to be included in future versions of STAMP€.

The first part describes the various satellite models that are used to translate a macroeconomic scenario into risk parameters at the bank level and into an impact on the banks' profitability or loss-bearing capacity. Chapter 4 gives details on the models and projections for the credit risk benchmark parameters. Chapter 5 presents the top-down models for retail interest rates on new business and wholesale funding rates, along with a tool to project banks' net interest margin. Chapters 6, 7 and 8 provide a description of the top-down models used for market risk, fee and commission income and operational risk, respectively. Finally, Chapter 9 presents the module used to project aggregate loan flows necessary for the dynamic balance sheet analysis. In this module, endogenous credit growth is estimated at the aggregate level in line with changes in macroeconomic variables.

The second part presents two models used to estimate macroeconomic feedback effects. The first one is a Dynamic Stochastic General Equilibrium (DSGE) model (Chapter 10), which allows the endogenous trend for macroeconomic and financial variables to be taken into account on the basis of a theoretical design of the preferences and constraints of households, firms and banks. The second model is a semi-structural Global Vector Autoregressive (GVAR) model (Chapter 11), which is used within STAMP€ to cross-check the links between de/over-leveraging and real activity.

The third part provides details on two contagion modules. STAMP€ includes first an interbank network modelling framework that facilitates an assessment of the risk of contagion spreading in the banking system, triggered by a shock to the ability of banks to pay back their debts (Chapter 12). The second set of contagion models focuses on cross-sector spillovers arising from the holdings of bank equity, with the sectors being interconnected in a network via holdings of financial instruments (Chapter 13).

The final part presents the future extensions of STAMP€. Chapter 14 presents first a top-down liquidity stress test framework modelling the interaction between banks' liquidity and solvency conditions. As the solvency of borrowers is also a key element that should be integrated into a top-down stress-testing infrastructure, Chapter 15 presents an integrated micro-macro model framework based on survey data to assess the solvency of households. To conclude, and looking ahead, Chapter 16 proposes further STAMP€ developments, including the modelling of banks' and financial market players' reactions to stressed conditions as well as the possibility of stress testing the financial sector as a whole. This would mean covering not only banks, but also shadow banks, insurers and pension funds, and central counterparties (CCPs).

We would like to express our gratitude to all authors of the subsequent chapters, who managed to conduct and finalise such rich and deep analytical work on top of their already demanding day-to-day obligations as ECB staff, in particular for stress-testing tasks besides other activities. We are also very grateful to Robert Köck and Monica Bermudez-Leyva who supported the book production process, as well as to the editing and publication teams of the ECB, without whom the completion of this work would not have been possible.

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Chapter 2 Stress-Test Analytics for Macroprudential Purposes: Introducing STAMP€

By Stéphane Dees and Jérôme Henry[11]

The macroprudential policy function has added a new dimension to stress testing that goes well beyond the examination of individual bank results. ECB staff has over the years developed a stress-testing framework for micro- and macroprudential purposes (see Henry and Kok, 2013). This chapter focuses on the macroprudential dimension of stress testing exercises and introduces the updated and extended stress-testing infrastructure. STAMP€ (Stress-Test Analytics for Macroprudential Purposes for the euro area) embeds various components that can be activated, for a given macro-financial scenario, in a centralised manner (otherwise called "top-down"). Beyond computing possible capital shortfalls for an individual bank under stress, which is commonly done also for microprudential purposes, the framework encompasses additional channels that are fundamental to macroprudential analyses, such as banks' reactions, contagion and feedback loops with the real economy. Further extensions include a liquidity stress test component and interactions with other parts of the wider financial sector. These additional analytical elements are described and corresponding simulation results provided, illustrating the extra information and value added of the extensions.

1 Introduction

The generalised use of system-wide stress testing has been boosted by the financial crisis starting in 2007. However, system-wide stress tests have so far focused on banks and their solvency, and have been mainly used for microprudential purposes.

The macroprudential policy function has added a new dimension to stress testing that goes well beyond the examination of individual bank results, as outlined by Constâncio (2015). In order to provide a macro dimension to stress testing exercises and make these suitable for macroprudential policy use, a system-wide stress-testing framework should account for macroeconomic impacts along the horizons of stress testing exercises, as well as alerting to the need for pre-emptive action and assessing the impact of macroprudential policy tools.

[11] With comments, suggestions and input from Anthony Bousquet, Maciej Grodzicki, Marco Gross, Grzegorz Halaj, Björn Hilberg, Dimitrios Laliotis, William Mehta, Cosimo Pancaro, Elena Rancoita and Fabrizio Venditti. The chapter also benefitted from useful comments from participants at the GRI-Fields Conference and Workshop on the Stability of Financial Systems: Modelling, Regulation and Stress Testing, June 27-29 2016, Toronto.

Top-down infrastructures have been already developed in a few institutions. For instance, in the context of the Financial Sector Assessment Program (FSAP) and the production of the Global Financial Stability Report, the IMF has conducted top-down stress tests of banks and insurance companies as well as liquidity risk analyses of banks and nonbanks (including insurance companies and mutual funds). This encompasses solvency and liquidity risks, as well as contagion risks. For these exercises the IMF uses a suite of models that can be categorised into three main approaches, namely, the accounting-based, the market price-based, and the macro-financial approach. The latter is key for macroprudential purposes and can be implemented with both accounting and market price data by estimating additional macro-financial linkage models ("satellite models") that directly connect macroeconomic assumptions and risk parameters (see Ong, 2014).

Central banks such as the Bank of England and the Bank of Japan have also developed top-down stress testing infrastructures for system-wide assessments. The Bank of England stress-testing framework for the UK banking system uses analytical tools to translate macroeconomic and financial scenarios into projections of bank profitability and capital ratios. For system-wide analyses, the Bank of England relies on a tool called Risk Assessment Model of Systemic Institutions (RAMSI), which incorporates feedback and amplification mechanisms from initial shocks, such as the interactions between institutions within the banking system or between the banking system and the wider economy (Burrows et al., 2012). The Bank of Japan uses a medium-sized model for stress testing, the Financial Macro-econometric Model (FMM), which incorporates real-financial linkages and also includes variables for individual financial institutions, such as capital adequacy ratios and profitability (see Kitamura et al., 2014).

The EU-wide stress testing exercises conducted by the European Banking Authority (EBA) are balance sheet-based, forward-looking assessments of bank solvency. The approach followed relies on the transmission of exogenous shocks (e.g. shocks to stock and bond markets and house prices that are consistently linked to the macroeconomic scenario) and shocks with an endogenous dimension (i.e. related to the impact of the scenario) to banks' credit risk, market risk, and other profit components. While the impact of liquidity stress is, to a certain extent, captured by the funding and liquidity shocks, the exercise remains primarily a solvency assessment.

There are a number of limitations to standard EU-wide or supervisory exercises, including a static balance sheet approach, no banks' reaction function, limited liquidity stress, the absence of interaction within the banking sector, such as externality effects, and the absence of interaction between banks and other specific sectors of the economy, in particular second-round effects and subsequent feedback effects within the financial sector and with the real economy.

Over the years ECB staff has developed a top-down stress-testing framework for micro- and macroprudential purposes (see Henry and Kok, 2013). Top-down macro stress tests are a powerful tool that can be employed in a range of exercises from the simplest – aimed at evaluating the direct impact of stress on each bank – to the most complex, when a test includes a dynamic balance sheet set-up and is combined with a macroeconomic model, thereby taking into account corresponding second-round effects. Also, for stress tests to be relevant from a systemic or macroprudential perspective, a variety of other contagion or spillover effects should be accounted for, reflecting interconnectedness within the financial sector, and across sectors and countries. In all cases, a key element of the framework should be the integration of the micro dimension into the macro approach, so that the latter is fully relevant.

This chapter focuses on the macroprudential dimension of stress testing exercises and is a first step towards operationalising the "vision" sketched out by Constâncio (2015). The paper presents updates and extensions of the ECB staff stress-testing infrastructure presented in Henry and Kok (2013), and introduces the resulting STAMP€, Stress-Test Analytics for Macroprudential Purposes for the euro area. By integrating, to a significant extent, the above-mentioned previously missing features, this new framework serves both micro- and macroprudential policy functions in a complementary manner. It has, in particular, the potential to support macroprudential policy in the design, calibration and assessment of the impact of macroprudential tools.

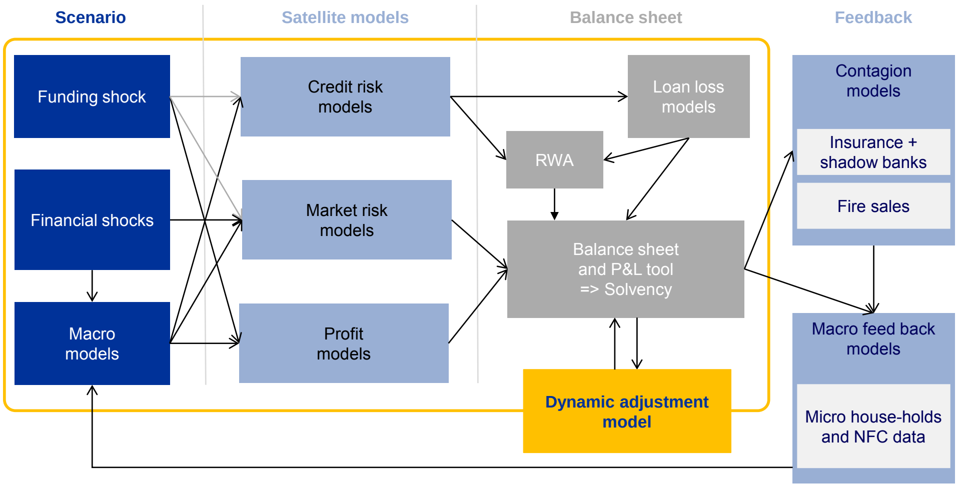
Section 2 provides an updated overview of the top-down stress testing framework developed and regularly used by ECB staff. Section 3 introduces the various dimensions to account for feedback effects, including second-round effects involving the macroeconomic environment and contagion impacts involving the banking sectors and other sectors. Section 4 gives an overview of the further extensions of the framework, including the addition of a proper liquidity stress test component and the integration, as much as possible, of other parts of the wider financial sector.

2 The ECB staff top-down stress testing framework – an overview

The ECB staff solvency analysis framework is a modular system with a four-pillar structure (see Chart 2.1). The first pillar (scenario design) consists of the design of the macro-financial scenarios to be applied to the banking sector; the second pillar (top-down satellite models) includes the modules used to translate the scenarios into variables affecting the valuation of banks' balance sheet components and banks' loss absorption capacity; the third pillar (balance sheet module) applies the projected profits and losses derived from the satellite models to individual bank balance sheets, calculating the resulting impact on each bank's solvency position. Finally, the fourth pillar (feedback modules) goes beyond the first-round impact on bank capitalisation to assess what the derived second-round effects of the initial bank solvency position might be in terms of contagion within the financial system and in terms of feedback effects transmitted to the real economy.

Chart 2.1

The four-pillar structure of the ECB staff solvency analysis framework



Source: Adapted from Henry and Kok (2013).

The top-down framework provides an effective steer within the quality assurance phase of microprudential stress testing exercises. Top-down stress tests, when carried out at the bank level, provide distributions of stress results across banks that can be compared bank-by-bank with the “bottom-up” results for the same banks – including results for different balance sheet and profit and loss items. A well-devised quality assurance process would typically include, as an important objective, some convergence between bottom-up and top-down results.

2.1 Macro-financial scenario design

The forward-looking solvency analysis of the banking sector begins with the design of a macro-financial scenario. That scenario needs to capture relevant systemic risks. Such risks are identified either in the ECB or the ESRB context (see Henry, 2015, for an overview of the process followed and related issues).

Systemic risks, which are often defined in broad terms and encompass several triggers with associated transmission channels, are mapped to exogenous shocks to real and financial variables. The choice of models and tools that support the calibration of macro-financial scenarios depends on the nature and horizon of a particular scenario. In the simplest setting, the size of shocks can be determined on the basis of historical time-series distributions. However, the use of more complex, model-based techniques leads to greater consistency across countries, and permits a more robust ex ante assessment of the likelihood of shocks materialising.

A comprehensive scenario of macro-financial stress usually extends several years into the future, which calls for the use of structural and time series models. Reduced-form VAR-type models are used to identify exogenous shocks to consumption, investment, and property prices. In addition, measures of fundamental house price misalignment (either current or prospective, that take baseline dynamics into account) can be used to inform the calibration. The impact of shocks in non-EU economies on EU economies is modelled primarily using NIGEM.[12] Inputs into NIGEM simulations are obtained using multivariate time series models – GVARs (Dees et al., 2007) – that estimate financial market spillovers.[13]

Financial shock simulations are based on non-parametric models in order to capture the non-normal features of financial data. The tool used in this context, called the financial shock simulator, relies on a smaller data sample and on simulated data. The main reason for using a non-parametric approach, not relying on any pre-defined model specification, is that scenarios often require shocks to many financial variables that are strongly interrelated.

The macroeconomic impact on EU economies is derived using the "Stress Test Elasticities" (STEs) provided by the ESCB and updated on an annual basis. STEs are a multi-country, EU-wide simulation tool and are based on the impulse-response functions of endogenous variables to pre-defined exogenous shocks. STEs also incorporate intra-EU trade spillovers.

2.2 Translation of scenarios via satellite models

Satellite models are used to translate a macroeconomic scenario into risk parameters at the bank level (e.g. credit risk, interest rate risk or market risk) and into an impact on the banks' profitability or loss-bearing capacity.

Credit risk parameters

The models and projections for the credit risk benchmark parameters provide the scenario-conditional trend for point-in-time probabilities of default (PDs) and loss given default (LGD) parameters (see Chapter 4). The benchmark parameters are derived as a function of the baseline and the adverse macro-financial scenario.

A Bayesian Model Averaging (BMA) technique is used to model and project the default rates (used as a proxy for PDs) at the individual country and portfolio levels. The BMA approach is applied to a large set of equations estimated for each dependent variable. The approach allows model uncertainty to be accounted for by selecting the best performing specification among various possible equations that differ according to their explanatory variables or lag selections.[14]

LGD parameters are projected using two approaches. For secured credit exposures, the expected recoveries relate directly to the value of their collateral (residential properties for household mortgage exposures and commercial properties for secured

[12] The National Institute Global Econometric Model developed by the National Institute of Economic and Social Research, available at https://nimodel.niesr.ac.uk/index-home.php.

[13] Equally, such financial spillovers can be estimated through simulations, without imposing a specific parametric form on the data.

[14] Details of the econometric methodology are provided in Gross and Población (2017a).

corporate exposures). For unsecured credits, LGD parameters rise by a fixed parameter, calibrated using expert judgment.[15]

Bank interest rate spread models

The top-down models are specified to project retail interest rates on new business and benchmark parameters for wholesale funding rates from bank-specific starting points (see Chapter 5). These models are then used to derive top-down projections.

As with credit benchmark parameters, the interest rate spread models follow a BMA approach. For each country/segment, interest rate spreads are specified as a function of a set of macro-financial variables that are assumed to be potentially usable as explanatory variables. The reference rate (swap rate or short-term money market interest rate) used to compute the spread is also one of the potential explanatory variables, which allows the effective pass-through of the reference (swap) rate to be different from one.

Net interest margin

The estimation of the relationship between banks' net interest margin (NIM) and macroeconomic and financial variables, such as yield-curve parameters or GDP, relies on a dynamic panel approach (see Chapter 5). As the lagged dependent variable also plays a significant role in the specification, the NIM dynamics show some persistence. The positive spread effect confirms the returns to banks from maturity transformation activity. The presence of the negative impact of a lagged spread squared on NIM points to some non-linearities suggesting, in particular, that the positive effect of a wider spread on the NIM declines as the slope of the yield curve becomes steeper. Finally, the positive relationship between real GDP and NIM shows how better macroeconomic conditions improve banks' interest earning opportunities, through increased credit.

Market risk

In addition to the financial shock simulator introduced in the previous subsection, which is used to derive market risk stress parameters, top-down models have also been developed for counterparty risk, credit valuation adjustment (CVA) losses, market liquidity reserve losses, and held-for-trading losses. The first three models are based on econometric estimation techniques, while the last model is based only on finance theory, given the lack of data (see Chapter 6).

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[15] Alternative approaches, such as using the correlation between PDs and LGDs as proposed in Hardy and Schmieder (2013), were explored but did not prove robust across EU countries.

Fee and commission income

The projection of fee and commission income is based on dynamic panel data that relate income over assets to macroeconomic and financial variables (see Kok et al., 2017, and Chapter 7). The explanatory variables include stock market returns and the short-term interest rate. As the lagged dependent variable is an important predictor, fee and commission income dynamics show some persistence. The positive relationship between stock market returns and fee and commission income may potentially reflect fees associated with stock market transactions (e.g. securities brokerage). Finally, fee and commission income is negatively affected by changes in short-term interest rates, suggesting that a fall in interest rates leading to a reduction in their interest margin obliges banks to search for other sources of income.

Operational risk

The operational risk module is based on the loss distribution approach, i.e. the compounding of frequency distributions (the number of events in one year) and severity distributions (the loss amount per event) to yield the aggregate loss distribution. The model assumes specific distributions for both frequency and severity that are applied to the reported data using an arithmetic moment matching method. Monte Carlo simulations are then run to produce the aggregate loss distribution (see Chapter 8).

2.3 Solvency analysis

The risk-specific results are aggregated to produce total impact on banks' annual profits using a balance sheet tool, and following accounting principles.

Pre-provision profits are aggregated as the total of banks' interest income, fee and commission income, trading income, other operating income and operating expenses. Net interest income, fee and commission income, and losses related to operational and market risk are estimated directly using the satellite models described in the previous section. Interest income is also adjusted for the loss of income on impaired assets. Other income is projected using historical distributions, where the specific percentile of the distribution employed in the projection is determined using expert judgment. Operating expenses are generally assumed to remain constant.[16]

After-tax income is then derived by assuming that profits are subject to a time-invariant corporate tax rate and that dividends are to be paid out of positive profits in line with historically-observed payout ratios.

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16 This assumption may be relaxed, in particular where the starting expenses are biased upwards due to one-off costs, or where banks are implementing restructuring measures leading to credible and tangible cost savings.

In addition, changes in the stock of bank capital are influenced by the revaluation of debt securities held in the "available-for-sale" portfolio. Risk exposure amounts are estimated, where possible, using regulatory formulas. For credit risk, this can be done at the individual country and portfolio levels, with the aim of replicating the regulatory calculation in a granular manner. The capital held for market risk is projected using multipliers calibrated using expert judgment on the basis of past regulatory stress tests. Capital charges for operational risk are generally held constant. It is assumed that the volumes and composition of exposures stay unchanged, and maturing exposures are replaced by exposures with a comparable risk profile.

The resulting impact on bank solvency ratios, under the baseline and adverse scenarios, can be used to derive bank capital shortfalls conditional on a pre-determined capital ratio threshold. It may also inform the assessment of banks' solvency and viability, as well as their financial soundness.

The top-down solvency results could be used in early warning exercises too, feeding usefully into bank-specific early warning systems such as that of Alessi and Detken (2011). This would provide a summary measure of financial sector fragility and the risk of a systemic financial crisis from a dynamic perspective, extending beyond the usual two to three-year stress test horizon.

In a broader macroprudential context, these top-down solvency results offer only a starting point for further analysis. They may serve as an input to models of banks' dynamic response to stress that helps gauge the potential amplification of economic stress via a number of feedback channels, e.g. from banks' deleveraging, the contagious impact on other banks, and cross-sectorial spillovers, the focus of the next section of this paper.

3 Accounting for feedback effects

3.1 Dynamic balance sheet and bank reaction function

While the EBA EU-wide stress test assumes a static balance sheet, a macroprudential perspective should take dynamic balance sheets into account so that the size and composition of banks' balance sheets varies throughout the scenario. This could be the result of mitigation actions after shortfalls or a reaction to a change in the economic environment. Indeed, banks' balance sheets change their composition due to the market conditions implied by the generic growth of credit and debt in the economy and valuation changes, but also due to a bank's strategic actions. These strategic responses to changing market and regulatory parameters need to be clearly understood in order to gauge the effectiveness of macroprudential policies and their influence on banking systems.

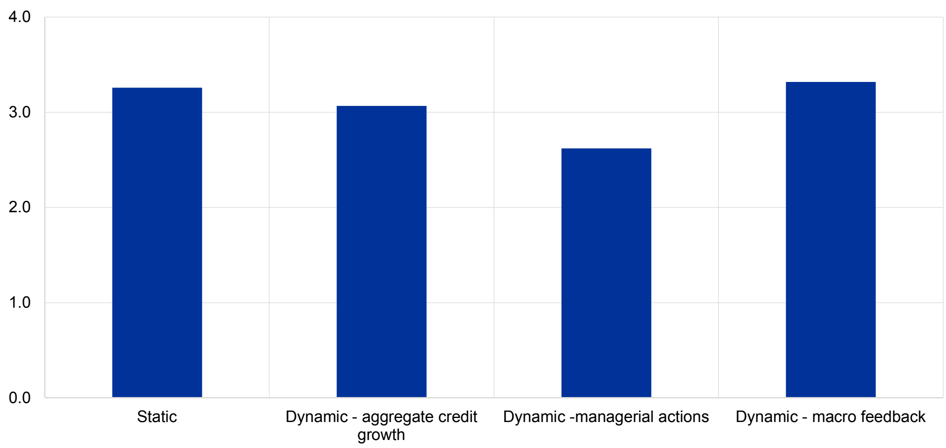
To account for feedback effects, as a first step the method followed in STAMP€ starts with endogenous credit growth estimated at the aggregate level, in line with changes in macro variables, such as GDP (see Chapter 9). It is then assumed that banks proportionally adapt their loan book size to the macroeconomic scenario. This top-down approach has, by construction, no impact on real growth and is the approach used by institutions like the Federal Reserve or the Bank of England when running their stress tests assuming a dynamic balance sheet.

Aggregate loan flow models are estimated for three portfolio segments (non-financial corporations, household mortgages and consumer credit) in 24 countries, linking flows of new lending to macro-financial variables (see Chapter 9). The choice of the flow of new lending instead of gross loan stock as a dependent variable is justified by a higher correlation with macroeconomic variables such as GDP. Loan flow data are also less distorted by non-macroeconomic factors such as loan transfers within financial groups, sales of loans to non-bank institutions, write-offs and prepayments.

The decline in the volume of bank lending is then used as input to the top-down stress testing model suite to obtain the corresponding adjustments to banks' profits, loan losses and risk-weighted assets. This reaction to the macroeconomic scenario may improve banks' capital in respect of the stress test simulation under a static balance sheet assumption (see the first and second bars from the left in Chart 2.2, for an illustration based on 2013 data) if the decline in risk weighted assets due to deleveraging more than offsets the implied decline in net interest income. A positive outcome compared with the static balance sheet assumption is, however, not guaranteed, a key assumption being the loan book quality. For instance, if all bad loans are assumed to remain on the balance sheet, the overall impact may be negative. More generally, the overall impact would depend not only on deleveraging assumptions, but also on bank data that are used, i.e. balance sheet composition matters (see the illustration based on the macroprudential extension of the EBA 2016 stress testing exercise, in Chapter 3).

Chart 2.2
Accounting for feedback effects in STAMP€

(CET1 ratio, %)



Notes: The bars represent the aggregate CET1 losses from stress (as a percentage of risk-weighted assets) under the static balance sheet assumption (first bar), a dynamic balance sheet taking into account aggregate credit growth (second bar), a dynamic balance sheet with the optimisation-based adjustment of banks' asset structures (third bar) and macroeconomic feedback with a macro model (fourth bar). These figures, based on 2013 data, are for illustration purposes.

As a second step, the approach followed in STAMP€ enables banks to decide, following an identified capital shortfall, how to actively deleverage, depending on the scenario, using an optimisation-based model. In this case, it is not only credit that will decline. Another, simpler, option would have been for banks to follow a pecking order, whereby non-core assets are shed before core ones. In the optimisation model, banks adjust their asset structure in response to shocks to the parameters (e.g. return, default probability, funding cost and capital level) of their asset and liability categories, as well as through changes to their solvency and liquidity constraints (see Hałaj, 2013 and 2016, and applications in Henry and Kok, 2013). The optimisation process is modelled as a mean-variance portfolio choice with risky funding sources and risk limits that require a bank to keep its capital ratio above the regulatory minimum and to hold enough liquid assets to cover a potential outflow of funding.

Without considering any externalities that may arise from lower aggregate credit, the banking system may then overall improve its solvency position following optimal individual banks' deleveraging decisions (see the third bar from the left in Chart 2.2). Indeed, the reactions of these banks do not account for second-round effects of aggregate deleveraging on real GDP. An estimation of these potentially adverse macroeconomic feedback effects is now presented.

3.2 Estimating macroeconomic feedback effects

The two previous steps have shown that allowing dynamic balance sheets may improve banks' capital ratios. However, downsizing balance sheets in isolation creates externalities at the aggregate level, which need to be taken into account. The last step that defines the link between banks' aggregate reactions and the macroeconomy relies on simulations of macroeconomic models to capture the effects of banks' deleveraging on the real economy.

Two types of macroeconomic models are used: a Dynamic Stochastic General Equilibrium (DSGE) model and a Global VAR (GVAR) model. Both models were calibrated for the euro area countries, allowing heterogeneity across euro area countries of banks' and private sector agents' responses (at the country level) to changes in the macroprudential and monetary policy stance to be taken into account.

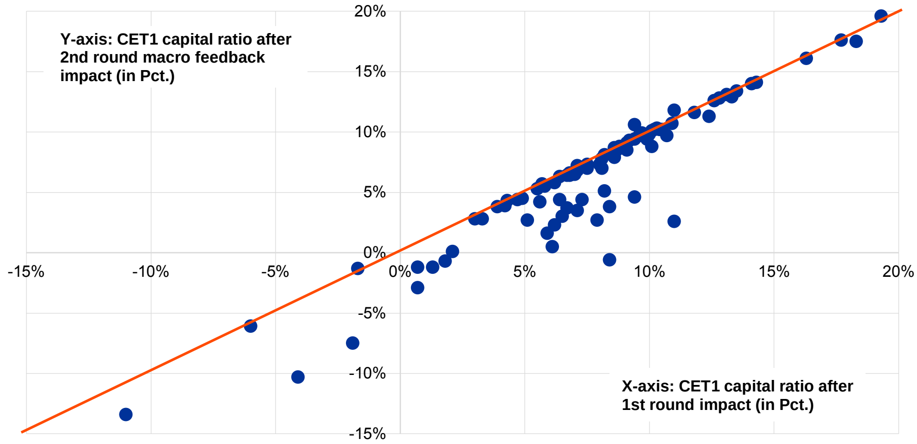
A DSGE is the first type of macroeconomic model used, as this type of model allows the endogenous trend for macroeconomic and financial variables to be taken into account, on the basis of a theoretical design of the preferences and constraints of households, firms and banks.

The DSGE model used in STAMP€ is a one-country model (see Darracq et al., 2011, and Chapter 10) with three agents (households, firms and banks) and two sectors, producing residential and non-residential goods. Banks are affected by three layers of financial frictions: first, banks face risk-sensitive capital requirements and adjustment costs related to their capital structure; second, they also have some degree of market power in the retail market, which results in the imperfect pass-through of market rates to bank deposit and lending rates; finally, due to banks' holding imperfect information regarding their borrowers and the resulting monitoring of their credit contract costs, firms and impatient households face external financing premia, depending on their leverage.

In the context of the stress test exercise, the DSGE models are used to assess macro-feedback effects. Stress test results fed into the model described above show that an adverse scenario triggers macro-feedback effects via three channels: capital shortfalls, loan supply effects and the impact on PD (affecting lending spreads). Illustrative simulations (see Chart 2.3) show that macro feedback generally leads to an amplification of the initial shock impact.

Chart 2.3

First-round losses under the adverse scenario versus second-round losses, taking macroeconomic feedback into account



Note: Simulation based on Darracq Pariès et al. (2011).

This final step in the relationship between banks' reactions and the macroeconomy shows that the deleveraging implied by the adjusted balance sheets leads to lower real GDP than in the scenario, thereby aggravating the capital position compared with the previous steps allowing dynamic balance sheets. The illustration in Chart 2.2 (see last bar) shows that the benefit of a dynamic balance sheet for capital is crowded out by the adverse effects of deleveraging, due to lower GDP.

Alternative modelling approaches are also used to cross-check the links between de/over-leveraging and real activity. STAMP€, therefore, also includes a Mixed Cross Section-GVAR (MCS-GVAR) model, as designed in Gross, Kok and Żochowski (2016) and detailed in Chapter 11. The MCS-GVAR model is estimated for the 28 EU economies and a sample of banks, and is used to assess the transmission of bank capital shocks to the rest of the economy. In particular, the model is used to assess how changes in the capital ratio affect bank credit supply and aggregate demand. In a subsequent paper, Gross, Henry, and Semmler (2017) also demonstrate non-linearity in the leverage-activity relation.

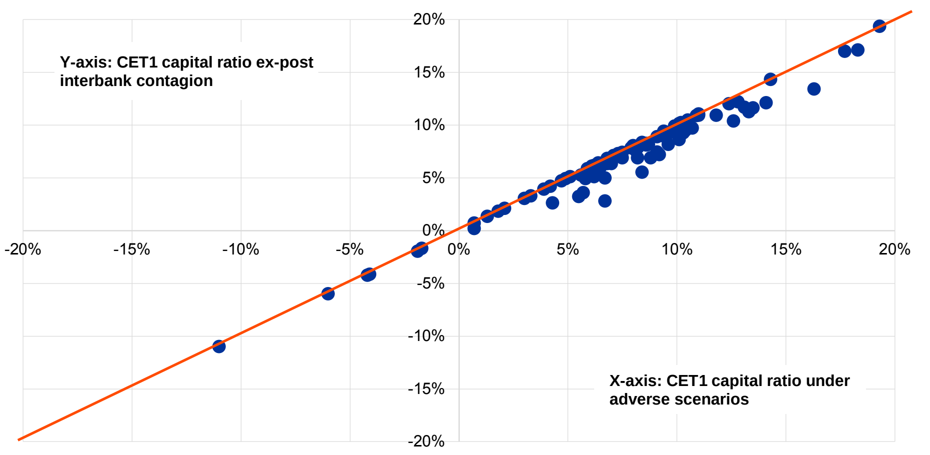
3.3 Estimating contagion impacts within the banking sector

Another second-round effect to be considered is contagion within the banking sector. A bank shortfall could lead to a default on certain claims, with spillovers to other banks which could, in turn, also default.

STAMP€ includes an interbank network modelling framework that facilitates an assessment of the risk of contagion spreading in the banking system, triggered by a shock to banks' ability to pay back their debts (see Chapter 12). The network of exposures is either given (based on ad hoc data collections, EBA 2011, or supervisory statistics – large exposure disclosures) or can be reconstructed on the basis of the aggregate figures for banks' interbank lending and borrowing. The shock is usually in the form of a reduction of capital (after a macro-financial adverse scenario has impacted banks' balance sheets). The knock-on effects are measured using a cascade process of defaults and reported as a capital ratio reduction. A key assumption is that the capital shortfall triggers a default. The framework can also include "fire-sale" effects, where it is assumed that banks will liquidate part of their portfolio to return to their capital positions before the shock.

Second-round effects captured using simulated interbank networks show that accounting for contagion effects indeed amplifies the impact of the initial shock (see Chart 2.4).

Chart 2.4
First-round losses under the adverse scenario versus second-round losses, taking interbank contagion into account



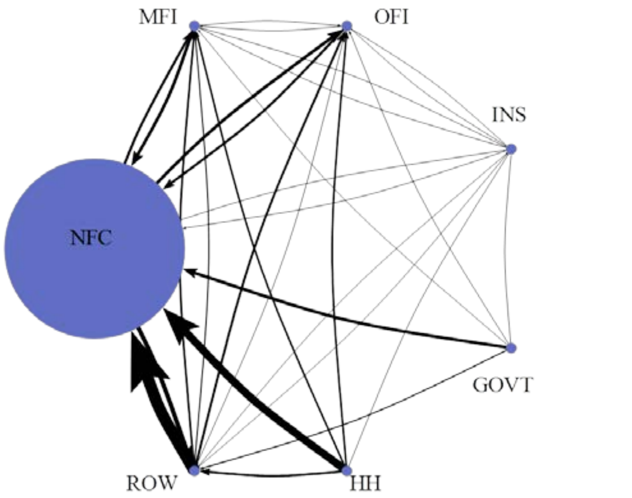
Source: Henry and Kok (2013).
Note: X-axis: end-2014 CT1 capital ratio under the adverse scenario (99th percentile); y-axis: CT1 capital ratio ex post interbank contagion (99th percentile).

3.4 Estimating cross-sectoral spillovers via flow-of-funds

The last channel of feedback effects included in STAMP€ relates to spillovers from the banking sector to the other sectors of the economy (see Chapter 13). The shock transmission reflects the fact that a decrease in the economic value of banks affects the prices of claims on those banks. In the most extreme scenario, bank failures and resolutions may lead to equity stakes being forfeited, and the significant impairment of debt claims. As a result, holders of claims on banks would be worse off, and the value of debt and equity instruments they have issued could decrease. Capital losses under stress are therefore translated into valuation losses for a given banking sector's stock prices, which are then reflected one-to-one in the asset valuation of other sectors (including non-financial sectors) holding banks' assets. This could also apply using, for example, insurers' stress test results. The impact on specific sectors can be calibrated using flow-of-fund data, available for each EU country on a quarterly basis and with a detailed breakdown for the assets and liabilities of individual sectors by instrument.

Financial account statistics are used to form sector-based networks for the study of cross-sectoral contagion effects. As data for the bilateral exposures in individual sectors are only partly available, missing links are constructed using simple maximum entropy techniques (Castrén and Kavonius, 2009).[17] Chart 2.5 gives an illustration of the resulting network.

Chart 2.5
Cross-sector shareholdings



Note: Based on Castren and Kavonius (2009) and Castren and Rancan (2013).

Shocks are transmitted to the rest of the system via mark-to-market losses in counterparty positions through equity holdings, and reverberate through the system until they reach those sectors that do not issue equity.[18] This process can be iterated until incremental effects are marginal. The final result reflects the relative weight of the bank equity holdings of each sector, as well as indirect exposure to bank equities through the holdings of equity in sectors that invest in bank equity.

Combining financial account data with individual bank and firm data facilitates the construction of bank-firm relationship networks. These can be used to study contagion arising from shocks to firms (or banks) and to assess how they affect other firms/banks in the network (Hałaj et al., 2014). This tool shows material differences across sectors in terms of the contagion effects inflicted on the banking sector (see Table 2.1).

17 Castrén and Rancan (2013) extend this approach to include the cross-border linkages of national banking sectors.

18 As the leverage of an individual sector increases, so does the riskiness of debt instruments issued by the sector. In principle, the mark-to-market spiral can be extended to losses on holdings of debt instruments, in line with the statutory hierarchy of claims, although the incremental impact in each round of losses on the valuation of debt instruments is not as automatic as in the case of equity instruments.

Table 2.1

Cross-sectoral spillovers – via flow-of-funds

	NFC	MFI	OFI	NMMF	INS	PF	GOV	HH	RoW
AT	10%	2%	17%	3%	3%	0%	7%	4%	7%
BE	2%	0%	2%	2%	0%	1%	1%	1%	1%
CY	17%	0%	16%	24%	1%	1%	7%	6%	11%
DE	3%	0%	2%	1%	1%	0%	2%	1%	1%
EE	0%	0%	0%	0%	0%	0%	0%	0%	0%
ES	0%	0%	0%	0%	0%	0%	0%	0%	0%
FI	2%	0%	2%	1%	0%	1%	1%	1%	1%
FR	2%	0%	1%	1%	0%	0%	1%	1%	1%
GR	9%	1%	5%	9%	1%	3%	13%	7%	4%
IE	11%	0%	2%	6%	4%	7%	8%	2%	6%
IT	3%	0%	1%	2%	1%	2%	2%	2%	2%
LU	3%	0%	2%	1%	0%	0%	2%	1%	2%
MT	0%	0%	0%	0%	0%	0%	0%	0%	0%
NL	1%	0%	2%	1%	0%	0%	1%	0%	1%
PT	5%	1%	6%	3%	1%	2%	3%	3%	3%
SI	6%	0%	5%	12%	2%	1%	8%	3%	2%
SK	0%	0%	0%	0%	0%	0%	0%	0%	0%
EA	4%	0%	3%	2%	1%	1%	2%	1%	3%

Note: Based on Castren and Kavonius (2009) and Castren and Rancan (2013).

The results should be interpreted with caution. There may be an upwards bias, as data for sectorial accounts are not consolidated, and the contagion loss may reflect intermediate losses for holding companies with the same ultimate beneficial ownership. Additionally, market valuations take forward-looking expectations into account and may therefore not be fully adjusting in line with the book losses that affect accounting equity.

4 Further extensions of the top-down framework

As shown above, STAMP€ accounts for the various channels of the transmission of shocks to banks and their spillover to the rest of the banking system and to the macroeconomy. The goal is to properly account for second-round effects when assessing the impact of these shocks on banks' solvency. Further improvements to the STAMP€ modelling framework of extensions are also ongoing to allow the stress testing of the liquidity situation of banks, and the solvency of borrowers (households and non-financial corporation) and the non-banking sectors.

4.1 Solvency-liquidity interaction

Solvency shocks may affect the liquidity situation of banks via a number of channels, even in the absence of defaults (e.g. through higher implied funding costs). Quantity rationing may also affect less well-capitalised banks or even banks with similar business or other features to those most affected by the stress. Collateral pricing and funding availability could also be sensitive to macroeconomic conditions.

Liquidity stress-testing infrastructures are usually designed on a stand-alone basis. However, for macroprudential purposes they should be linked to solvency stress tests (see Chapter 14). Propagation channels between liquidity and solvency are common and may be integrated within a liquidity stress testing framework (Basel Committee on Banking Supervision, 2015) that mainly uses the above network analysis combined with additional features, in order to encompass channels like fire-sale externality, margin calls and the closure of funding markets, credit rating, asset quality and pricing.

This liquidity stress test extension is needed since past crises were fundamentally linked to a liquidity and contagion-related chain of events. Understanding the underlying mechanisms should be a pre-condition of any policy response, especially if this is aimed at being sufficiently pre-emptive, i.e. preventing or capping the damage caused by a particular crisis rather than ex post “mopping up the mess” (Jeanne and Korinek, 2013). It can moreover be safely assumed that central bankers, and not only supervisors, should show a deep interest in liquidity stress tests. The modelling challenges relate to: scenario design (market or institution specific), translation of the scenarios into projections of liquidity positions, data gaps (insufficient and inadequate reporting), the embedding of contagion mechanisms, quantification of the feedback loop between liquidity conditions and the solvency position of banks, and behavioural responses to the shock and its impact on market liquidity and funding conditions (Hałaj and Henry, 2016).

Technically simpler but more granular quasi-accounting approaches (see Chapter 14) are also needed to complement the analysis, considering, for example a detailed approach to effectively available collateral and therefore asset encumbrance, also allowing us to compute regulatory ratios such as Liquidity Coverage Ratio (LCR) or Net Stable Funding Ratio (NSFR). This approach is needed especially to carefully assess the need and the availability of central bank funding to a given entity, before a liquidity squeeze and forced sales occur.

Simulations conducted (network-based) show that the accumulation of transmission channels gradually transforms a local weakness into a systemic failure, due, in particular, to the solvency-liquidity interaction. There is, however, a time dimension issue, as liquidity events develop and crystallise much more quickly than solvency-triggered events.

4.2 Stress testing households and non-financial corporations

Stress tests usually focus on the solvency of lenders. However, the solvency of borrowers is also a key element that should be integrated into a top-down stress testing infrastructure. This is important for many reasons, including assessing banks’ non-performing loans, the dynamics of consumer credit, and the impacts on housing markets that reinforce the link between the real and the financial cycles. In order to properly assess the solvency of borrowers, there is a need for granular information at the household and non-financial corporation (NFC) levels.

With regard to households, although the collection of new data is not yet complete (Anacredit), the use of household surveys could be useful. The Integrated Dynamic Household Balance Sheet (IDHBS) Model (Gross and Población, 2017b, and Chapter 15) makes use of a rich dataset – the EU-wide survey of households – which enables us, when connected to additional macro models, to generate a path for employment, loan demand and also default parameters for each specific household.

The model can be used, for example, to generate alternative PDs conditional on a given scenario, helping to cross-check other models such as the core model used in EBA stress-tests. It can also be used to assess the granular impact of macroprudential measures such as loan-to-value/loan-to-income steps, based on micro data.

Concerning non-financial corporations (NFCs), preliminary research is available using CDSs of large firms and their link with those of banks, which provides an illustration of the main stylised facts and transmission channels. Further research is, however, needed at a more granular level, using the survey data for a large sample of NFCs.

4.3 Stress testing of non-banking sectors

The non-banking financial sector has grown substantially over the past decade, especially in some segments, sometimes performing bank-like functions. The stress testing of non-banking sectors is also an important feature of a top-down stress test infrastructure (see Chapter 16).

Integrating banks and the shadow banking sector

With steady growth in assets and the potential for substituting financial services from the regulated sector, shadow banks constitute a challenge for any macroprudential policymaker, representing a new risk area. This observation calls for a more holistic approach to the structure of the euro area financial sector going forward, requiring the modelling of second-round effects on the banking system via impacts on liquidity and asset prices.

A structural approach should be added to STAMP€, with the ultimate aim of making the price response endogenous within an integrated bank-shadow-bank stress test framework using an agent-based modelling framework. Ari, Kok, Darracq Pariès and Żochowski (2016) suggest that the shadow banking sector has a natural tendency to grow until it becomes systemically important to the entire financial system and endangers the stability of the banking sector. The illiquidity of shadow banks may not be accommodated by banks due to the respective size of the two sectors or regulatory constraints.

Stress test on Central Clearing Counterparties

A final area for further extensions concerns stress testing the central clearing counterparties (CCPs). Most transactions have to go through CCPs due to regulation, which significantly affects the topology of banking system networks and creates a systemic connection between banks and CCPs. Although there has already been some attempt to stress test the CCPs by ESMA, there is a need to further develop scenarios which are specific and linked to the liquidity situation of CCPs. There is also a need to go further in modelling the impact of CCPs. Such models should not only include solvency and liquidity stress but also account for interconnectedness via common exposures to clearing members, as well as possible knock-on effects on the banking sector that could arise if the guarantee fund of a CCP were wiped out and clearing members were required to cover the CCP losses.

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Chapter 3 Applying STAMP€ - a macroprudential extension of the 2016 EU-wide stress test

By Maciej Grodzicki, Gabriel Gaiduchevici, Marco Gross, Krzysztof Maliszewski, Elena Rancoita, Rui Silva, Sara Testi, Fabrizio Venditti and Matjaž Volk

As illustrated by the recent EU-wide stress test conducted by the EBA, the estimated impact of an adverse scenario can be quite severe.[19] For the 37 largest euro area banks included in the 2016 EU-wide stress test, the aggregate Common Equity Tier 1 (CET1) capital ratio is expected to drop by 390 basis points under the adverse scenario, from about 13.0% in 2015 to about 9.1% at the end of 2018.

At the same time, these sizeable effects cover only first-round stress impacts on banks' balance sheets. They do not account for the endogenous reaction of banks to anticipated higher capital needs, nor for the interaction of banks with one another and with other economic sectors. In addition, the EBA stress testing methodology is based on a static balance sheet assumption, whereby the total volume and composition of all bank asset and liability items should remain unchanged over the stress test horizon, and maturing items should be replaced by identical positions. The modular framework of STAMP€, which connects several standalone models and tools, has the capacity to deliver a more complete and enriched picture of what the overall macrofinancial impact of stress on the banking sector could represent, by incorporating additional amplification channels.

The results presented here should, nonetheless, be treated as illustrative, given that some of the findings discussed in this chapter rely, to a large extent, on specific and possibly strong assumptions which would call for further robustness analyses.

1 Structure of the macroprudential extension

The objective of the macroprudential extension is to account for several effects that cannot be captured in a bottom-up setting where it is the responsibility of individual banks to project their solvency and profitability, without access to the results of other banks in the system.

The macroprudential extension begins by relaxing the static balance sheet assumption. This assumption is not consistent with the macroeconomic scenario of the exercise, which implies that the volume of credit follows macroeconomic developments, although, pragmatically, it allows comparability and a level playing

[19] For a detailed presentation of the aggregate results at the EU level, see EBA (2016b).

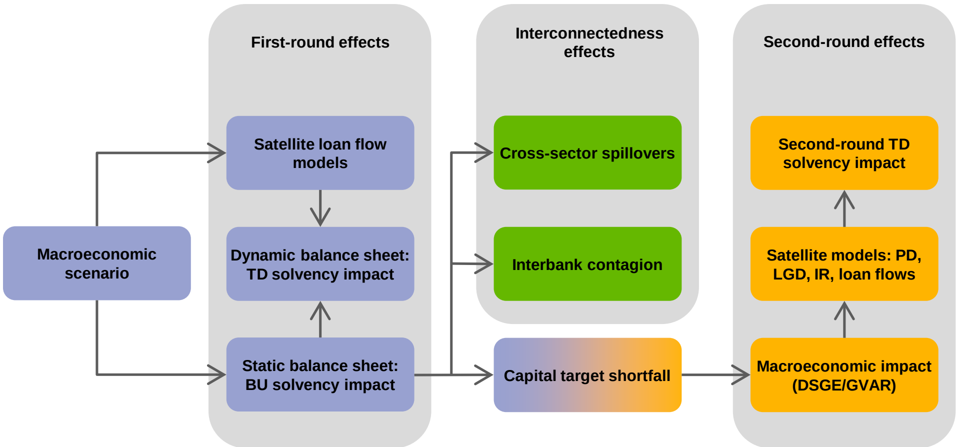
field. It also facilitates the quality assurance of the results, which otherwise would be very challenging. Under this assumption, and following the EBA methodology, banks calculate the first-round impact of the scenario on their solvency. In a macroprudential extension, the dynamic balance sheet assumption is preferable, leading to an outcome consistent with the macroeconomic scenario. In this illustrative application of STAMP€, the dynamic balance sheet assumption is introduced for the stock of loans to the non-financial private sector (see the left-hand side of Chart 3.1), with corresponding adjustments being made to the liability side of the balance sheet.

After taking into account the changing credit needs of the economy, banks may find that they are unable to withstand the adverse scenario. They could attempt to increase their capital ex ante, for example by constricting new lending or raising capital from external sources. Individual banks' responses, aggregated at the system level, could reach systemic proportions and give rise to second-round effects. A negative credit supply shock, for instance, would translate into lower consumption and investment, which would, in turn, impact on all macro-financial variables. The deterioration of the macroeconomic environment would further worsen bank asset quality and reduce pre-provision profitability, thus eroding bank capital further (see the right-hand side of Chart 3.1). No further management actions, such as cost reduction, are considered in this illustrative application.

In addition, the macroprudential extension aims to analyse the potential spillovers arising from the interconnectedness of banks through money market exposures, and cross-holdings of financial instruments by various economic sectors (see the middle part of Chart 3.1).

Chart 3.1

Structure of the macroprudential extension of supervisory stress tests



Source: ECB.
Notes: BU: bottom-up (banks' results), TD: top-down, IR: interest rates.

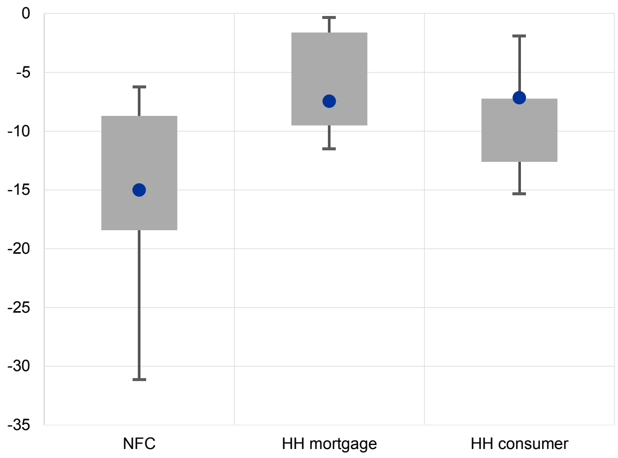
2 Loan volume adjustments under the adverse scenario

The first step of the macroprudential extension is to estimate the impact of changes in the stock of aggregate bank loans on bank solvency, thus removing a part of the inconsistency introduced by the static balance sheet assumption. Credit growth may be expected to be weaker under the adverse scenario than under the baseline scenario. The flow of credit is a function of the macroeconomic variables (and vice versa). On the one hand, credit demand may fall during a recession, while on the other, banks facing capital and funding constraints might reduce credit supply. Risk would also play a role, as some potential borrowers might become too risky under conditions of macroeconomic stress. Aggregate loan flow models (see Chapter 9) are used to project the size of credit portfolios at the bank level, consistent with the baseline and adverse scenarios.

Chart 3.2

Total loan stock change

(difference between three-year growth rates, adverse scenario to baseline scenario; percentage points; boxes: interquartile range across EU countries; dots: EU aggregate; black lines: range between the 10th and the 90th percentile.)



Source: authors calculations.

An application of these models to the 2016 EU-wide stress test scenario is shown in Chart 3.2. This shows that the scenario-conditional rates of change of new loan flows at the consolidated bank level differ significantly between the baseline and the adverse scenarios across all portfolio segments, with the gap being particularly large for the non-financial corporate portfolio. Large euro area banks would reduce their stock of corporate loans significantly, on aggregate, by about 15% over the three-year period compared with baseline levels. Credit to the household sector would be a little less strongly affected by the worsening macro-financial conditions, as mortgages and other consumer lending would shrink by about 9% compared with baseline.

The impact of changes in the volume of bank lending on the capital position of the banks is assessed using the ECB staff top-down stress testing tools.[20] The loan flow model returns a conditional forecast of changes in the aggregate, economy-wide flow of new loans (including rollovers of existing loans) to households and NFCs. These economy-wide changes are applied in order to project loan flows in each portfolio for all banks covered by the exercise, applying multiples to the full-year flow of loans reported for 2015. It is assumed that credit exposures to general governments, central banks and institutions remain constant. This simplifying assumption may be somewhat conservative, given that these exposures might also be expected to fall under the dynamic balance sheet assumption. For example, a shrinking balance sheet would reduce the need to hold high-quality liquid assets in the LCR framework, thus potentially triggering a reduction in exposures to the central government.

[20] See Chapter 2 and Henry and Kok (2013).

Banks' profits, loan losses and risk exposure amounts (risk-weighted assets) are adjusted to align with projected loan flows. This requires a number of departures from the EBA stress testing methodology. [21] For instance, caps on total net interest income become irrelevant, as the total net interest income should be allowed to increase with increasing lending volumes. Similarly, the end-2015 floors for risk exposure amounts are replaced by floors for portfolio-level risk weights. Apart from these adjustments, it is assumed that no additional management action, such as internal restructuring, the reduction of operating expenses or the disposal of unprofitable business lines, would be taken. The changing volumes would only affect performing loans, while defaulted loans are assumed to remain – following the EBA methodology – in default and would not be written off over the projection horizon.[22]

The changes in other balance sheet items, such as securities holdings, derivatives, and liabilities, are derived in this illustrative application of STAMP€ from simplifying assumptions. On the liability side, the total absolute change in funding requirements, stemming from the changing size of the loan book, is assumed to be distributed pro rata across all non-derivative liabilities by the non-renewal of maturing liabilities. The composition of liabilities will remain constant, i.e. it is assumed that banks will fund their assets with the same liability mix as that observed at the cut-off date. Should there be a shortage of maturing positions within a particular class of liabilities, the pro rata assumption is enforced nonetheless, implying the execution of a de facto buy-back operation by the bank (albeit without additional costs being incurred). Derivative assets and liabilities, as well as associated income and expense projections, are held constant. It is also assumed that banks will maintain the same level of holdings of debt securities.

The impact of the introduction of the dynamic loan flow projections on aggregate CET1 capital ratio is not clear-cut. Some banks may be able to benefit from lower loan flows through a reduction in capital requirements and future impairments, while others could become worse off as a result of their operating profits being reduced. On aggregate, the latter effect is expected to prevail.

Looking more closely at the main drivers of the dynamic balance sheet results, the overall capital ratio would be supported through a lowering of risk exposure amounts and, to a lesser degree, credit losses, as the absolute size of loan books is expected to contract. However, the reduction in net profits, especially interest income, would work in the opposite direction. The dynamic response of banks may therefore, on a net basis, have a counterproductive effect, as some banks would be weakened by their own deleveraging. This would reduce future profits with a total reduction in the CET1 ratio of up to about 15 basis points (see Chart 3.3).

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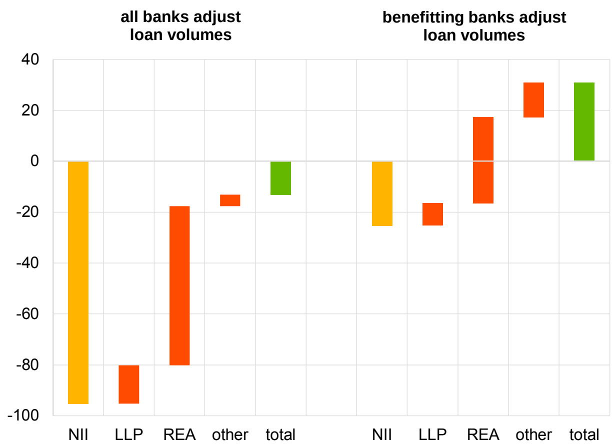
[21] For details of the EBA bottom-up stress test methodology, see EBA (2016a).

[22] Allowing for the resolution of non-performing loans (NPLs) would introduce a significant source of uncertainty into the exercise, as the bank solvency impact would depend on the assumed terms under which non-performing loans would be liquidated. In principle, the disposal of NPLs would also be expected to reduce the regulatory capital requirement and would slightly reduce the flow of interest income, as the positive carry on the unprovisioned part of the NPLs would not materialise.

Chart 3.3

Contributions to the difference between the CET1 ratio under the static and dynamic balance sheet assumptions

(basis points of the aggregate CET1 capital ratio)



Source: authors calculations.
Notes: NII – net interest income, LLP – loan loss provisions, REA – risk exposure amount, other – factors other than NII, LLP and REA.

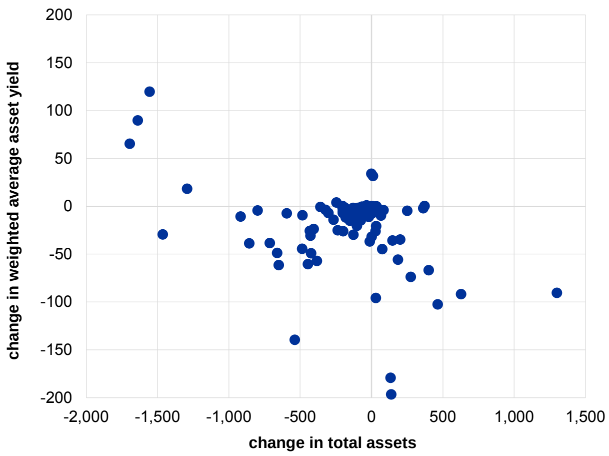
An additional sensitivity analysis was therefore carried out to identify the potential aggregate improvement in solvency ratios were banks only to reduce assets if they benefited from lower business volumes. In that case, which equates to an assumption of perfect foresight on behalf of banks and which abstracts from the likely loan demand constraints (exogenous to bank business decisions), the aggregate solvency ratio would increase by about 30 basis points. Even then, total net interest income would be slightly lower than in the static case, but the difference would be more than offset by a reduction in capital requirements.

The projected fall in net interest income is, to a large degree, driven by volume effects. However, the changing composition of the loan book also supports a drop in net interest income. Weighted average asset yields are forecast to fall, pointing not only to deleveraging but also to a de-risking of bank exposures under the loan volume projections adopted (see Chart 3.4). Although the decrease in weighted asset yields would be more pronounced for those few banks which expanded their balance sheets, it is clear that many banks would reduce their exposure to high-yielding assets – a reflection of the significant reduction in corporate lending under the adverse scenario. Following on from the pro-rata assumption adopted for liabilities, this composition effect is not present on the liability side and the weighted average cost of liabilities varies by no more than 25 basis points between the static and dynamic balance sheet results (see Chart 3.5)

Chart 3.4

Weighted average asset yield by bank

(basis points)

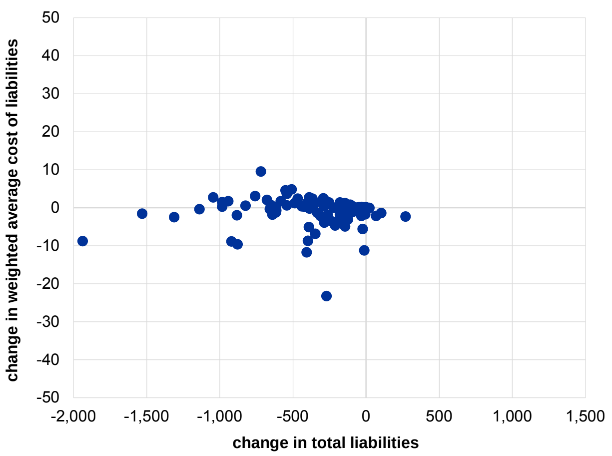


Source: authors calculations.

Chart 3.5

Weighted average cost of liabilities by bank

(basis points)



Source: authors calculations.

An alternative approach to the economy-wide loan flow models, at the micro level, is based on the theory of portfolio optimisation.[23] Subject to regulatory capital and liquidity constraints, it is assumed that banks will periodically adjust their asset structures with the aim of maximising risk-adjusted returns on capital. The optimisation procedure results in changes to each bank's asset composition, as well as movements in bank asset allocations between cash, securities and loans. An aggregation of individual banks' projections leads to economy-wide changes in loan stocks.

3 The macroeconomic consequences of banks' response to stress

If the response by banks to the macroeconomic scenario involves the upfront adjustment of their capital ratios to conform to a given target capital ratio, it would probably result in an additional contractionary loan supply shock for euro area economies – seen as a potential second-round effect (see Chart 3.1). The magnitude of that shock would depend on the adjustment strategy adopted by the banks and on the desired capital level under stress.

The target capital ratio could be determined by the supervisor, as in the case of the 2011 and 2014 EU-wide stress testing exercises, or it could be an internal bank target. In the latter case, the target may be set with the objective of reassuring bank investors – creditors and shareholders – as to the safety and soundness of the bank, thus reflecting market discipline and benchmarking against stronger banks. The choice of capital target has a direct impact on the extent of the economic impact – the higher the target, the more severe the consequences of banks' adjustments could be for the economy. In this context, the supervisors usually set targets that are below the current overall capital requirements, which include combined buffer requirements. Countercyclical buffer rates could be reduced in that case, as cyclical risks would materialise and buffers could be drawn down to absorb their impact. As an illustration, this chapter considers two thresholds: 6% and 8% CET1, which are higher than the previous supervisory targets used in the EU-wide stress testing exercises.

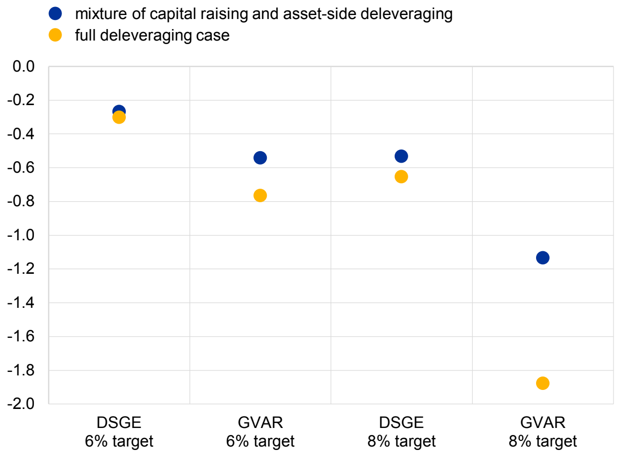
The nature of banks' adjustments plays a key role in the calibration of the second-round effects. If banks have access to capital markets and it is possible to cover the capital needs identified by the stress testing exercise by selling new stock, the second-round effects will not be significant. However, this option is often not open to weaker banks during times of macro-financial stress and further deleveraging may be required through a reduction in assets. In this illustration, it is assumed that banks may choose one of two strategies to increase their capital ratio upfront, with a view to adjusting to the materialisation of stress and achieving a desired capital level. The first strategy achieves the adjustment through a reduction in assets (a full deleveraging strategy) and basically assumes that capital markets are closed to

[23] For details of this approach, see Hałaj (2013).

banks. The second strategy replicates the historical bank response to stress and involves a combination of a reduction in assets and an increase in capital from external sources.

Chart 3.6
Impact of bank reaction on euro area GDP

(percentages, deviation from baseline levels, end-2018)



Source: authors calculations.

In order to estimate the macroeconomic effects of adjusting to a higher capital target, the macroprudential extension can use two macroeconomic models. The first is a Dynamic Stochastic General Equilibrium (DSGE) model.[24] In this model, the capital needs are treated either as a shock to the capital ratio target, leading to both an increase of equity and a reduction of credit, or as a shock to bank mark-ups, which, directly, only reduces the supply of loans. These results are complemented by simulations based on a semi-structural Global Vector Autoregressive (GVAR) model[25], where the capital needs are translated into either shocks to the actual capital ratio[26] or shocks to the credit supply only, reflecting a full asset-side deleveraging scenario in the latter case. In both cases, the initial capital needs have an impact on the domestic economy, which is then transmitted to other euro area economies through the trade channel (and in the GVAR to an additional extent via the cross-border supply of credit through direct lending).

This distinction between the combined effect of deleveraging and raising equity on the one hand, and a full deleveraging strategy on the other hand, is critical with regard to the impact on the economy, with the second strategy leading to a significantly stronger loan supply shock and, therefore, more severe second-round macroeconomic effects than the first strategy.[27] On aggregate, if banks' adjustments follow their historical pattern of increasing capital ratios, this may reduce euro area GDP by about 0.2% to 0.5% in 2018, compared with the baseline, for the 6% capital target (see Chart 3.6). The full deleveraging approach would result in a GDP reduction of between 0.3% and 0.8%.

The use of two different models is aimed at reducing misspecification risks. However, as demonstrated, it could also lead to significant differences in the resulting projections. Conceptually, one of these models is a general equilibrium model while the other is a semi-structural model involving sign constraints for the purpose of identifying the credit supply shock scenario. Additionally, the GVAR model captures,

24 See Chapter 10 and also Darracq Pariès et al. (2011) and Darracq Pariès et al. (2015).

25 See Chapter 11 and Gross, Kok and Żochowski (2016).

26 Note that while the capital target is shocked in the DSGE model, in the GVAR model it is assumed that the actual capital ratio is shocked.

27 For a more detailed discussion of the differences between these two strategies see Gross, Kok and Żochowski (2016), Behn et al. (2016) and Gross, Henry and Semmler (2017).

in an endogenous fashion, trade and financial cross-border spillovers, while the DSGE model results reflect only trade spillovers.[28]

4 Second-round impact on banks

The deterioration of macroeconomic conditions, set in motion by the banks' ex ante adjustments to a higher capital target under stress, is likely to increase the impact on bank solvency still further. It is also likely to affect, through trade and financial channels, banks that would otherwise not have needed to adjust to a higher target, including banks operating in countries where otherwise not a single bank would have needed to adjust. These second-round effects are in addition to the impact of the dynamic adjustment of loan volumes to changing macro-financial conditions, representing a supply-side effect that arises from an endogenous response of banks that expect they are unable to meet a specific capital target.

The top-down stress testing tools employed at the ECB translate the second-round macroeconomic effects into an impact on bank solvency. Credit risk parameters – probability of default and loss given default, as well as interest rate parameters and loan flows – are re-calculated under the revised macroeconomic scenario, using the models presented in Chapters 5 to 9. The additional reduction in the solvency ratios can be obtained following the top-down procedure outlined in Chapter 2.

Bank solvency stress may, additionally, trigger the materialisation of liquidity risk – both idiosyncratic (bank-level) and system-wide – even if there are no bank failures. Weaker banks may experience funding outflows which, in turn, could prompt a further reduction in lending, in addition to the second-round effects deriving from adjustment to a higher solvency ratio (as discussed in the previous section). This feedback loop between liquidity and solvency, which is not currently modelled[29], may further weaken the banking sector.

The top-down solvency results could also be used in early warning exercises. Bank-specific and country-level early warning systems[30] can provide an estimate of the probability of a bank or a country being affected by financial distress for up to two years beyond the three-year horizon of the stress test. At the banking sector level, this would provide a summary measure of financial sector fragility and the risk of a systemic financial crisis from a dynamic perspective, reaching beyond the usual stress test horizon.

[28] Trade spillovers are not modelled directly in the DSGE setting, which uses a closed economy approach, but are estimated separately using Stress Test Elasticities, a multi-country tool based on macroeconomic models of ESCB central banks.

[29] See Chapter 14 for the discussion of the liquidity stress testing approach in STAMP€ and of the models of links between solvency and liquidity.

[30] For example, see Lang (2016) and Alessi and Detken (2011). See also Behn et al. (2016), in which the authors integrate an early warning model based on an indicator of systemic banking crises with a GVAR model as referred to earlier in this section.

5 Contagion and spillovers

Apart from the second-round effects that derive from the endogenous response of the banking sector to stress, an adverse scenario is likely to trigger further bank losses related to the interconnectedness of individual banks and cross-sector spillovers. Banks are directly exposed to each other through several financial instrument types: secured and unsecured loans, holdings of debt securities and equity, and holdings of derivatives. Some of these claims may become impaired in the event of a bank resolution or an outright failure – this is more probable for shareholdings and unsecured credit claims (both debt securities and loans). Moreover, other economic sectors may be affected by bank stress, in particular in their role as shareholders in the banking sector.

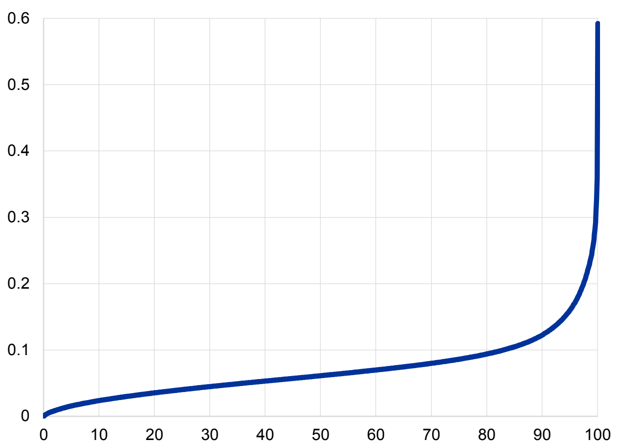
5.1 Interbank contagion

The stress test data do not enable identification of the bilateral exposures of participating banks or cross-holdings of bank bonds and bank stocks. Only aggregate data are available for the interbank exposures of each bank to banks located in selected countries.

Chart 3.7

Direct interbank contagion does not lead to sizeable second-round losses

(x-axis: percentile of the distribution, y-axis: euro area bank losses on interbank exposures to banks falling below the 6% threshold; percentage points of CET1 ratio)



Source: authors calculations.

This data constraint is tackled using the random network approach of Hałaj and Kok (2013) described in Chapter 12. The random network model was calibrated using the total exposures per bank collected from the stress test data. It was assumed that the first-round solvency impact would trigger losses on interbank exposures to all banks falling below a prescribed threshold. The group of banks that would be expected to default on their interbank liabilities includes banks which would initially remain above that threshold, but fall below it as a result of their exposure to weak banks. Banks would additionally sell debt securities to maintain a constant leverage ratio, and this would lead to a second-round price effect that would affect the entire system. This approach may be viewed as highly conservative for two reasons. Credit risk mitigation provided by collateral (such as government bonds pledged in repo transactions) or other guarantees cannot be taken into account due to data constraints, although it would significantly reduce losses in the case of actual stress. Additionally, interbank exposures are generally protected by a layer of other claims in the hierarchy of creditors, such as Additional Tier 1 and Tier 2 capital.

The random network model indicates that the possible reduction of the capital adequacy ratios as a result of interbank contagion amounts to more than 20 basis points in fewer than 2.5% of cases at the sample level. At the aggregate level, the CET1 ratio reduction at the 90th percentile is estimated to be 12 basis points and the median reduction is 6 basis points (see Chart 3.7). This outcome seems consistent with developments in the banking sector since the global financial crisis, including a decrease in interbank exposures, and with the characteristics of the data sample (the largest, most resilient European banks).

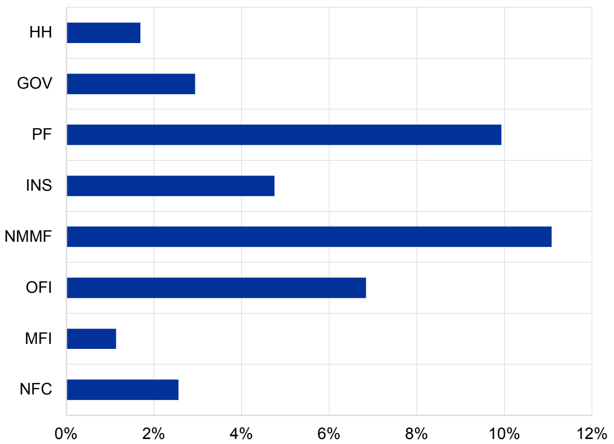
5.2 Cross-sector spillovers

Cross-sector spillovers are estimated using the country-level financial and non-financial accounts of the economic sectors, according to the European System of Accounts (ESA 2010) methodological framework (see Chapter 13). These sectors are interconnected via holdings of financial instruments issued by a given sector, thus forming a closed and internally consistent system. Bilateral exposure data are available for listed shares and investment fund shares/units – two of the three instruments used to shape the network used in the contagion analysis. The third instrument (unlisted shares) is not covered in the so-called who-to-whom accounts and the relevant matrix can be estimated on the basis of the distribution of holdings of listed shares.

Chart 3.8

Cross-sector spillovers would mainly affect the non-bank financial sector

(losses triggered by the reduction in market value of bank equity; euro area aggregates, percentage of total financial assets)



Source: authors calculations.
Note: NFC: non-financial corporations, MFI: monetary financial institutions, OFI: other financial institutions, NMMF: non-money market investment funds, INS: insurance companies, PF: pension funds, GOV: general government, HH: households, RoW: rest of the world.

The spillovers arise from the holdings of bank equity. In the first round, the market value of bank equity decreases as the banking sector recognises losses under the adverse scenario. It is assumed that price-to-book ratios remain unchanged. This means that if a sector experiences an adverse shock to the book value of its equity, this loss of equity value is transmitted, through mark-to-market accounting, to those sectors which hold that equity on the asset side of their balance sheets.[31] In turn, the shareholders of sectors affected in the second round pass the losses on to their shareholders, and this propagation continues until the incremental spillovers in the subsequent round become negligible.

Non-bank financial institutions, in particular investment funds and pension funds, are most strongly affected by the equity shock to the banking sector (see Chart 3.8). They may lose up to around 10% of the total value of their financial assets at the euro area aggregate level. Households and non-financial corporations are less severely affected.

[31] See Castrén and Kavonius (2009).

6 Conclusions

Supervisory stress testing exercises, such as the EU-wide bank stress testing exercise, may be unable to cover important effects related to the changing credit needs of the EU economy under the considered adverse scenario of the exercise and to idiosyncratic bank responses to changing conditions and adjusted capital targets.

This chapter offers an illustration of how STAMP€ can be used to capture these effects. If the static balance sheet assumption is relaxed and credit aggregates are allowed to follow the path implied by macroeconomic developments, banks' vulnerability may be greater than in the case of a static balance sheet. This deterioration may be exacerbated by bank-specific deleveraging, initiated by weaker banks aiming to comply with a self-imposed capital target under stress. Such behaviour may be enforced by market discipline even if the regulator does not set a specific capital hurdle rate. Contagion and cross-sector spillovers, as well as feedback between solvency and liquidity, may further amplify the impact on banks.

The application of STAMP€ presented does not include the full extent of the modular framework. The household balance sheet model, presented in Chapter 15, will be added to the framework to analyse the effects of bank distress on the household sector and, in turn, on the credit risk related to mortgage lending in particular. This model, based on micro survey data, provides an alternative to the econometric satellite credit risk model for household mortgages discussed in Chapter 4. It may also offer insights into the impact of macroprudential borrower-based policy measures – caps on loan-to-value ratios and debt service-to-income ratios – which were put in place in several euro area countries. Such instruments could trigger a loan demand shock, whose impact on the household sector and the economy can then be quantified using the GVAR macro model (or a DSGE model) – the use of which is illustrated in Chapter 15. Likewise, the links between bank solvency and liquidity risk, outlined in Chapter 14, may be added to this application, so that the impact of the projected deterioration of bank solvency on bank funding conditions, along with the resulting changes to bank funding composition and pricing, can be more accurately reflected in the results of the macroprudential extension.

The range of applications of STAMP€ is not restricted to an analysis of the macroprudential effects of bank distress. The framework could be adapted, with some modifications, to provide an assessment of the impact of the resolution of non-performing assets on the health of the banking sector and the economy. It may also be used to forecast the impact of a low interest rate environment, complementing existing analytical work, such as that presented by the ESRB.[32]

[32] See ESRB (2016).

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SATELLITE MODELS

Chapter 4 Credit risk satellite models

By Marco Gross, Oana Maria Georgescu and Björn Hilberg[33]

This chapter presents the methodology that has been used for developing top-down satellite models, with a specific focus on credit risk (CR) parameters, that is, country and loan portfolio-level probabilities of default (PDs) and loss given default (LGD) parameters. The parameter paths, derived from the satellite models, form the basis for projecting bank loan losses conditional on a macro-financial scenario. For the LGD parameters, a structural model is involved for housing-related portfolio segments, i.e. for the non-financial corporate real estate and the household mortgage loan portfolios. A Bayesian model averaging (BMA) technique has been employed to develop the PD satellite models, which, in total, comprise several hundreds of bridge equations linking these risk parameters to macro-financial variables.

The credit risk satellite model system plays a crucial role in the overall stress test model suite (along with the BMA-based bank interest rate model package, presented in Chapter 5), as the risk of borrowers defaulting and not repaying their loans is one of the most material risks that banks face and for which they ought to build up an adequate level of loan loss reserves. It is, therefore, particularly important that the credit risk models are developed in a robust manner, to ensure that they provide precise estimates for PD paths conditional on an assumed macro-financial stress scenario. Quantifying the impact of this major channel is thereby needed for any macroprudential stress-test application.

The chapter is divided into three parts. Sections 1 and 2 present, respectively, the PD and LGD model frameworks. Some illustrative scenario projections implied by the models are presented in Section 3.

1 Probability of default (PD) models

The PD satellite model suite delivers scenario-conditional forward paths of the CR parameters for 48 countries and regions around the world, including 28 European Union (EU) countries. In terms of portfolio segmentation for the PD models and projections at the country level, a distinction is made between six portfolio segments: non-financial corporate (real estate-related and non-real estate-related), exposures to households for house purchase, consumer credit to households, financial corporate loan exposures and banking book loan exposures to sovereigns.

[33] The models presented in this chapter have benefited from useful discussions with, and feedback from, various national competent authorities and national central banks in the euro area and non-euro area EU countries in the course of the model development work for the 2014 and 2016 EU-wide stress tests.

1.1 Default rate data

Two main data sources served as a basis for developing the PD satellite models (and continue to be used to re-estimate the models on a continuous, at least annual to bi-annual, basis):

1. Historical default rate series obtained from national competent authorities across the EU countries, which provided the data in the course of past stress test exercises to the ECB;
2. Moody's KMV model and Kamakura-based indicators of expected default rates for financial corporations and sovereigns respectively.

With regard to the first item, three different types of default rates or proxies thereof are included in this part of the default rate database: i) realised default rates based on credit registers; ii) default rates derived at the portfolio level based on non-performing loan (NPL) flows[34]; and iii) bankruptcy filings-based default rates for non-financial corporations. While PD models should preferably not be based on bankruptcy filings-based default rates, the latter are employed in a few cases to enlarge the data and model basis. The reasons why bankruptcy filings-based default rates are not optimal are at least twofold: i) these default rates tend to be count-based, while the preference is for volume-based default rates; and ii) they have a company perspective, in the sense that they measure insolvency, while the preference is for default rates from the bank perspective which capture a past-due event, which does not necessarily imply that companies would be insolvent (hence an X-day past due measure of payment delay is the more timely and relevant measure for credit risk models). The first category of data covers the non-financial corporate segment and the household loan segment for both housing and non-housing-related loan exposures.

PDs for financial corporations – sourced from Moody's KMV (Credit Edge) – are Merton model-type PDs whose main inputs include measures of leverage and asset volatility, which are derived from the market value, and volatility of equity and the amount of combined long and short-term debt of a bank.

For sovereigns, the PDs are sourced from Kamakura, a firm that is specialised in credit risk modelling techniques. One of their models is a logistic model for sovereign defaults encompassing a large sample of sovereigns from around the world, including, as predictor variables, a wide range of macroeconomic and political factors. Certain factors, such as political factors which are known to be contained by the models of Kamakura, are not included in the BMA as potential predictors, mainly for the reason that it would add to the burden of defining baseline paths and adverse deviations for these additional variables. Kamakura model-implied historical PD measures were taken as a basis to develop the BMA satellite equations, thereby mimicking, though not exactly replicating, Kamakura's models.

[34] NPL flows are derived by controlling for write-offs and asset sales to thereby obtain a suitable default flow proxy.

Both the financial and sovereign expected default rate measures represent “real world” PDs, which can also be referred to as “physical” PDs, and thereby stand in contrast to what are known as “risk-neutral” PDs. Risk-neutral PDs can, for instance, be derived from credit default swaps (CDS). The caveat associated with the latter approach is that CDS-implied PDs also reflect the market price of risk and, as a result, their change is at times unrelated to a change in the fundamentals of the financial institution or a sovereign. Moreover, risk-neutral PDs, in particular for large banks, tend to be lower than their real-world counterparts (and also differ with respect to their dynamics over time) because they reflect the presence of implicit or explicit state guarantees. Thus, overall, real-world PDs seem preferable as a basis for a satellite model system to be used for scenario analysis and stress testing.

A Bayesian Model Averaging (BMA) econometric technique is employed for modelling and projecting the default rate measures at the individual country and portfolio levels.[35] The BMA approach operates with a pool of equations (several hundreds or thousands) per dependent variable, to which weights are assigned that reflect their relative predictive performance, which then results in a “posterior model” equation.[36] The pool of equations contains a large number of equations for every single credit risk indicator (per portfolio segment and geography), by considering all possible combinations of predictors from a pool of potential predictor variables, including variables such as real GDP, investment, consumption, exports, price inflation, short- and long-term interest rates and others.

The rationale for using a BMA technique, in particular, for modelling credit risk measures such as default rates is at least twofold. First, there is considerable uncertainty as to what the drivers of credit risk dynamics are. Being agnostic and employing a model search technique makes it possible to take a conservative approach to this uncertainty. Second, time series for credit risk measures such as default rates are typically short, thus an all-encompassing multivariate model including all potential predictors cannot be set up. General-to-specific model structuring methods are therefore likely to be inferior because the general model is bounded in its dimensions from the beginning and therefore prone to suffer from some omitted variable bias.

An Autoregressive Distributed Lag (ADL) model structure is the basis for defining the model space for all credit risk indicators for the BMA methodology. A dependent variable Y_t is allowed to be a function of its own lags as well as contemporaneous and possibly further lags of a set of predictor variables X_t^k:

$$Y_t = \alpha + \rho_1 Y_{t-1} + \cdots + \rho_p Y_{t-p} + \sum_{k=1}^{k_i} \left(\beta_0^k X_t^k + \cdots + \beta_{q^k}^k X_{t-q^k}^k \right) + \varepsilon_t$$

For the default rate, Y_t is defined as the logit level of a default rate y_t, that is,

35 See Gross and Población (2017). The methodology that has been employed to develop the models is known as a Bayesian Averaging of Classical Estimates (BACE) method; see Sala-I-Martin et al. (2004).

36 The predictive performance can be measured either in-sample or out-of-sample. The latter would be ideal for various reasons but often cannot be employed since the available time series for credit risk parameters are typically short.

$$Y_t = \ln y_t - \ln(1 - y_t)$$

The logit transformation guarantees that the predicted/projected default rate will not leave the [0-1] interval once the logit forward path is converted to PD space using the sigmoid (logistic) function, the inverse of the logit.[37]

The model space is constructed by considering all possible combinations of predictors from a pool of *K* variables, with the dimension of the models set to a self-defined limit *L*, which is usually set to at least four (time series length allowing).[38, 39] When all combinations of variables in models with *L* predictors are considered, the number of models *I* can be computed as:

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

The number of predictor variables appearing in a specific model is denoted as k_i, with $i = 1, \dots, I$ being the model counter.

For each specific model *i* with its predetermined set of predictor variables, the lag structures for autoregressive and distributed exogenous terms, p and q^k, are chosen optimally by estimating all combinations of lag structures up to a limit *G*. The specification for which the Bayesian Information Criterion (BIC) is minimal is chosen. When searching for the optimal lags, the lag structures for the autoregressive part and for lags of exogenous predictors are forced to be “closed” (without gaps).[40]

The model structure can be summarised in terms of Long-Run Multipliers (LRM) with respect to a predictor variable X^k from a model *i* in the model space. The LRM is defined as follows.

$$\sum_{l=0}^{\infty} \frac{\partial E(Y_{t+l})}{\partial X_t^k} = \beta_0^k + \cdots + \beta_q^k / (1 - \sum\nolimits_{i=1}^{p} \rho_i) \equiv \Theta^k$$

where α_i are the autoregressive model coefficients from a posterior BMA model equation.

Summarising the coefficient estimates on contemporaneous and distributed lags of a predictor variable in one multiplier facilitates the interpretation of the model structure. Moreover, it is useful to base the LRMs on normalised coefficients. A normalised coefficient is computed by multiplying the initial coefficient estimate by the ratio of the standard deviation of the predictor variable and the standard deviation of the dependent variable. The resulting coefficient estimates, and hence the normalised

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37 The sigmoid function is: $y = \exp x\,/(1{+}\exp x)$.

38 This maximum dimension *L* is set such that the largest model dimension, considering also all distributed lags that are being allowed for the exogenous model variables still implies sufficient degrees of freedom for estimation.

39 Should the number of potential predictors in some applications become very significant (say larger than 30), then stochastic search techniques can be employed instead of a fully exhaustive model space estimation.

40 It means that if, for example, two lags for a particular exogenous predictor variable were found to be optimal one would not exclude the intermediate first lag.

LRM, are thereby scale-free and comparable in magnitudes across model variables (i.e. portfolio segments and countries).

The individual equations in the model space for any given dependent variable are subject to a set of sign restrictions that are imposed on the LRMs of the predictor variables. For illustrative purposes, Table 4.1 summarises the type of sign constraints that can be imposed on the potential predictor variables in the respective portfolio segments.

Table 4.1
Predictor inclusion settings and sign constraints

	GDP growth	Private consumption growth	Investment growth	Export growth	Stock price growth	Unemployment rate changes	Price inflation	Long-term interest rate spreads (to DE)	Short-term interest rate
NFC-RE	-1		-1	-1	-1		-1	1	1
NFC-non-RE	-1		-1	-1	-1		-1	1	1
HH-HP	-1	-1				1	-1	1	1
HH-CC	-1	-1				1	-1	1	1
FIN	-1				-1		-1	1	1
SOV	-1						-1	1	1

Notes: NFC-RE and NFC-non-RE: real-estate-related and non-real estate-related non-financial corporate loan segment. HH-HP: loans to households for house purchase. HH-CC: consumer credit. FIN: financial institutions. SOV: sovereign banking book exposures.

A "1" or a "-1" denotes that the respective predictor variables are allowed to appear in the model equations for a dependent variable that is listed in the first column of the table, with the values indicating a positive or negative sign on the long-run multiplier of the predictor. No entry in the table means that the predictor variable can be excluded a priori on economic grounds. GDP, private consumption, investment, exports, and consumer prices are in that example allowed to enter the models as year-on-year growth rates. Long-term interest rates are 10-year benchmark government bond yields. The table indicates, for instance, that the sign on GDP growth is constrained to be negative, meaning that an adverse GDP scenario path below the baseline should imply a positive adverse-baseline gap for the model-implied forward path for the expected default rate.

Once estimated for the various segments and across countries, the models can be used to produce conditional density forecasts of all PDs over a scenario horizon, as a function of some baseline and adverse macro-financial scenario.

An option is to employ some different percentiles, possibly above the median, of the resulting conditional density forecast for the PDs at the country/segment level, to reflect the uncertainty in the scenario-conditional forward path of PDs. The rationale for choosing such a conditional quantile above the median would be to reflect residual, coefficient and model uncertainty, which are likely non-negligible in particular when short data samples are used to develop the models.

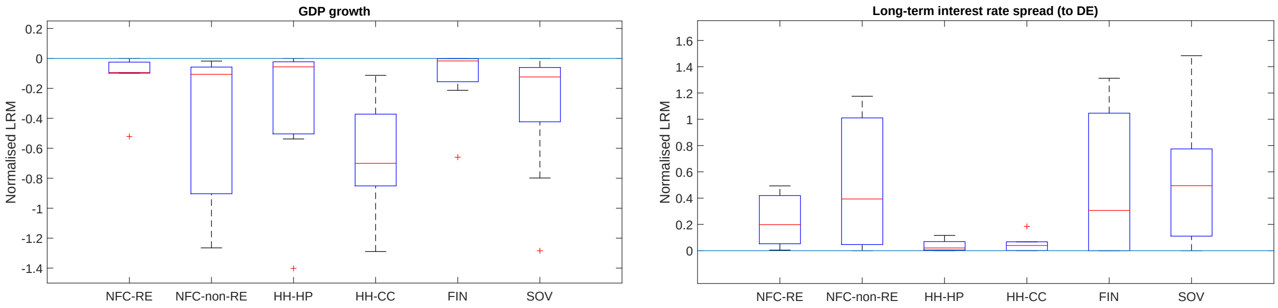
Across countries and segments, the acceptance of a model has to be conditional on its compliance with basic econometric and economic criteria, such as in-sample R-squares being sufficiently high or Durbin-Watson (DW) statistics falling into reasonable ranges. Non-compliance with any such standard criteria leads to the exclusion of a candidate model.

Charts 4.1 and 4.2 visualise illustrative cross-country (EU28) distributions of the normalised long-run multipliers (N-LRMs) for all relevant portfolio segments. The N-LRMs in Chart 4.1 for instance suggest a negative relationship between PDs and GDP growth across all portfolio segments. The relationship appears to be more pronounced for the NFC non-real estate (non-RE) segment and for the consumer credit segment, while for financial institutions, for instance, the link is less visible. The PDs' dependence on long-term interest rate spreads is positive, in particular for the NFC non-RE, financials and sovereign portfolios.

Chart 4.1

Normalised long-run multiplier (N-LRM) distribution on GDP growth and long-term interest rate spread

(multiples of standard deviations)



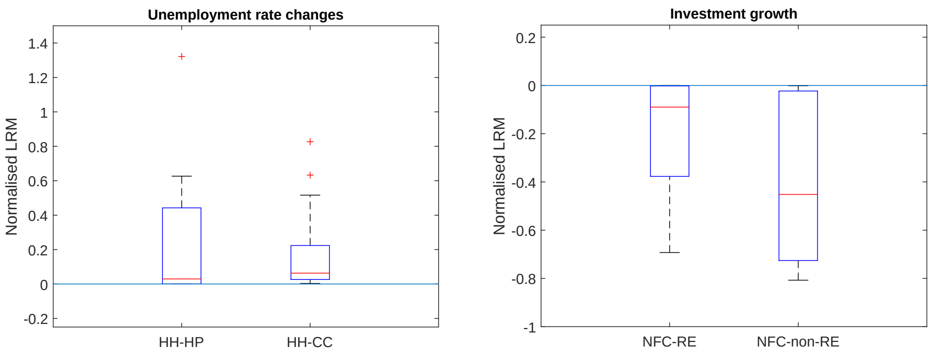
Notes: The box plots visualise the cross-country (cross-model) distribution of the normalised long-run multipliers (LRMs) linking the default rates at the country and segment levels with the predictor variables indicated in the header of the two charts.

An additional illustration is provided in Chart 4.2 for unemployment rates and investment growth. The N-LRMs for the household mortgage (HH-HP) and consumer credit (HH-CC) segment are of comparable magnitude.

Chart 4.2

Normalised long-run multiplier (N-LRM) distribution on unemployment rate changes and investment growth

(multiples of standard deviations)



Notes: The box plots visualise the cross-country (cross-model) distribution of the normalised long-run multipliers (LRMs) linking the default rates at the country and segment levels with the predictor variables indicated in the header of the two charts.

Concerning the sovereign PD model, an alternative to the econometric model-based approach that was presented in this section has been considered in the past, which entails a two-step procedure. First, a statistical link is established between long-term sovereign bond yields and sovereign credit ratings, by means of which a long-term interest rate scenario can be translated into a rating change conditional on a scenario. Second, these rating changes are linked to corporate through-the-cycle PDs conditional on the rating grades. The caveats of this approach relate primarily to the second step, where it is sub-optimal to proxy sovereign PDs by corporate PDs. Moreover, it is not optimal to employ through-the-cycle PDs for a PD that is meant to be a point-in-time estimate for its use in expected loss calculations.

1.2 PD parameter paths for countries/segments with missing data

For a number of countries and portfolio segments, the historical default rate data is either missing or insufficient to develop robust satellite models. The parameter paths for the missing countries and segments can be derived using the models that are available for the other countries in the same segment; which is an approach that can be referred to as "cross-filling". A median, for instance, can be taken over the available multi-model forward paths for a given scenario.

For non-European countries, a different approach is employed. Based on the projections for the European countries, bridge equations have been developed that link the default rate change with trends in real GDP. The reason for choosing only GDP to establish the link to the scenario lies in the fact that for the non-EU set of countries and regions only a reduced set of macro-financial variables is available in the scenario, including real GDP, price inflation, short-term interest rates and foreign exchange rates. GDP has been judged to be sufficient and serves as a synthetic indicator of the scenario to establish the link for non-EU countries.

Overall, the approaches for cross-filling the parameter paths for countries without models, both inside and outside the EU, are not optimal and it would instead be ideal to have the historical time series of the risk parameters for all relevant geographies. However, it is a viable solution and preferable to not including these countries in the assessment.

1.3 Bank-specific PDs and implied NPL dynamics

As a general principle, to derive bank-specific PDs, the top-down parameter paths are attached to bank starting points with a locational perspective. This means, for instance, that for the exposure of a German bank in Italy, the Italian model and its projections will inform the forward path for the Italian portfolio's PD parameter of the German bank. To attach the top-down PD parameter paths to bank and portfolio-specific starting points, an adjustment scheme has been developed whose use entails a twofold objective and implication: first, the PD paths for banks with their own country segment level PD starting point standing above (below) the system aggregate starting point (which the top-down satellite model is based on) will be less (more) steep in relative terms along the scenario horizon; second, the adjustment scheme guarantees that the scenario-conditional PD paths will never leave the 0-1 interval under any scenario (be it a benign or severe scenario).

Specifically, the starting point attachment for PDs works as follows.

(a) Convert the top-down satellite model's PD starting point (*T0*) for country *i* and portfolio *j* as well as the expected default rate forward path along the horizon $PD_{i,j}^{year,TD}$ to a distance-to-default measure $DD_{i,j}^{year,TD}$:

$$DD_{i,j}^{year,TD} = -\Phi^{-1}(PD_{i,j}^{year,TD})$$

where Φ^{-1} denotes the inverse of the standard normal cumulative distribution function.[41]

(b) Compute the absolute change of the distance-to-default measures under a scenario along the horizon (year):

$$\Delta DD_{i,j}^{year,TD} = DD_{i,j}^{year,TD} - DD_{i,j}^{T0,TD}$$

Take the bank- and portfolio-specific starting point $PD_{i,j}^{T0,bank}$ and convert it into a distance-to-default measure:

$$DD_{i,j}^{T0,bank} = -\Phi^{-1}(PD_{i,j}^{T0,bank})$$

(c) Apply the absolute changes in distance-to-default obtained in step b) to the bank- and portfolio-specific starting point:

$$DD_{i,j}^{year,bank} = DD_{i,j}^{T0,bank} + \Delta DD_{i,j}^{year,TD}$$

(d) Convert the distance-to-default measures obtained in the previous step back to a PD:

$$PD_{i,j}^{year,bank} = \Phi(-DD_{i,j}^{year,bank})$$

where Φ is the standard normal cumulative distribution function.

In conjunction with a path for an LGD at the bank and portfolio levels, the $PD_{i,j}^{year,bank}$ can subsequently be used to compute the expected loss.

The sovereign banking book is treated differently, that is, instead of employing the starting point adjustment method, the absolute PD trajectory, without any link to the banks' own starting point estimate of the sovereign PD, is set for all banks. The reason for doing so is based on the rationale that there should be no heterogeneity and hence no different estimates for the point in time PD of any one sovereign at a given point in time.

The scenario-conditional forward paths for PDs at the bank level drive the performing and non-performing loan stock dynamics. The gross loan stock, $\mathrm{L_t} \equiv \mathrm{P_t} + \mathrm{NPL_t}$, moves period by period at a gross loan growth rate *g*, that is $\mathrm{L_t} = (1 + \mathrm{g})\mathrm{L_{t-1}}$. The

[41] A logistic function or a probit or any other transformation that ensures boundedness on the 0-1 interval can be used instead of the inverse normal.

aggregate dynamics reflected by *g* mask various underlying processes, including new business, periodic repayment of principal (up to the point where loans fully mature), the move of loans from performing to non-performing status, and write-offs of loans from the NPL stock. The NPL stock dynamics look as follows:

$$\mathrm{NPL_t = NPL_{t-1}(1-w_t) + PD_tP_{t-1} - Cure_t}$$

The performing loan stock, on the other hand, evolves as follows:

$$\mathrm{P_t = P_{t-1}(1-r_t-PD_t) + NB_t + Cure_t}$$

The NPL stock at the end of period *t* equals the previous period's NPL stock, which decreases at the write-off rate *w*, reflecting the portion of loans from the NPL stock that the bank removes from its balance sheet when it does not expect to receive any further proceeds. The PD term is aligned with the conditional forecasts resulting from the PD satellite models. The Cure term reflects the amount of loans that move from the NPL to the performing loan category. The repayment rate *r* reflects the portion of principal of the performing loan stock at *t-1* that is repaid and therefore subtracted from the performing loan stock by time *t*. The term NB denotes new business, i.e. newly granted loans through period *t*, whose paths are determined by the loan flow models that are presented in Chapter 9.

2 Loss given default (LGD) model

A structural LGD model approach has been developed for the housing-related loan portfolios. The model does not require any historical data except for recent starting points as a reference point in time for LGDs at the country level. The primary mechanism of the structural LGD model is to align the value of loan collateral with the evolution of house prices in the scenario. Specifically, the value of commercial real estate collateral is aligned with commercial property prices (CPP) and the value of residential real estate with residential property prices (RPP). The LGD is computed as follows:

$$\mathrm{LGD = (\,(1 - Probability\ of\ Cure)\ \cdot\ LGL\,) + Costs}$$

The LGL variable represents the loss-given-liquidation and costs refer to administrative costs. The LGL can be derived from the loan-to-value ratio LTV and the assumed sales ratio (SR) upon liquidation. The sales ratio is expressed as follows:

$$SR = \mu\left[\Phi\left(\frac{LTV-\mu}{\sigma}\right) - \Phi\left(\frac{-\mu}{\sigma}\right)\right] + \frac{\sigma}{\sqrt{2\pi}}\left[e^{-\frac{\mu^2}{2\sigma^2}} - e^{-\frac{(LTV-\mu)^2}{2\sigma^2}}\right] + LTV\left[1 - \Phi\left(\frac{LTV-\mu}{\sigma}\right)\right]$$

where LTV denotes the indexed LTV at the assumed point of sale, μ the average expected sales ratio, σ the standard deviation of sales ratio distribution and $\Phi(.)$ the cumulative probability distribution function of the standard normal distribution. The average expected sales ratio μ is calibrated to the starting point LGD at the country level. The sales ratio is derived assuming that the recovery value is normally distributed and capped at the loan value. Given that the recovery value is the product of the collateral value and the sales ratio, and using the definition of the loan-to-value ratio, the formula for the recovery value can be solved analytically and yields the expression above.

A house price move in a given scenario can be incorporated either incrementally year-by-year over a scenario horizon, or be "front-loaded". When aligning the house price changes period by period, then the collateral valuation changes are indexed directly with the changes in the residential or commercial property indices in the scenario. The yearly decrease in house prices leads to an increase in the LTV and therefore the LGD over the projection horizon:

$$LTV(t) = LTV(0) \ * \frac{HP(0)}{HP\ (t)}$$

The "front-load" option would instead apply the cumulative house price change over the scenario horizon to LGD entirely in the first year, with no further change afterwards, thereby mirroring the assumption of "perfect foresight" of house prices in the scenario.

The property price evolution represents the LGD's direct link to the assumed macro-economic scenario. For the purpose of the calculation, a starting cure rate assumption (say 40%) can be employed across all countries along with an assumption for costs (say 5%). The cure rate would also be assumed to drop under an adverse scenario. The starting point LTV can be calibrated at the country level using the exposure-weighted LTVs reported by banks. Finally, the standard deviation σ of the sales ratio distribution also needs to be set, for instance at 20%.

For the non-real estate segments (NFC non-RE and HH-CC), the fixed multiplier can be employed, which would be used to multiply the starting point LGDs for these portfolios by a scenario-independent factor. An alternative approach relying on the correlation between the PD and the LGD could also be taken, which may however be difficult to empirically justify. For sovereign banking book exposures, a fixed absolute percentage can be assumed, e.g. 40%.

3 Illustrative scenario-conditional forecasts for PDs and LGDs

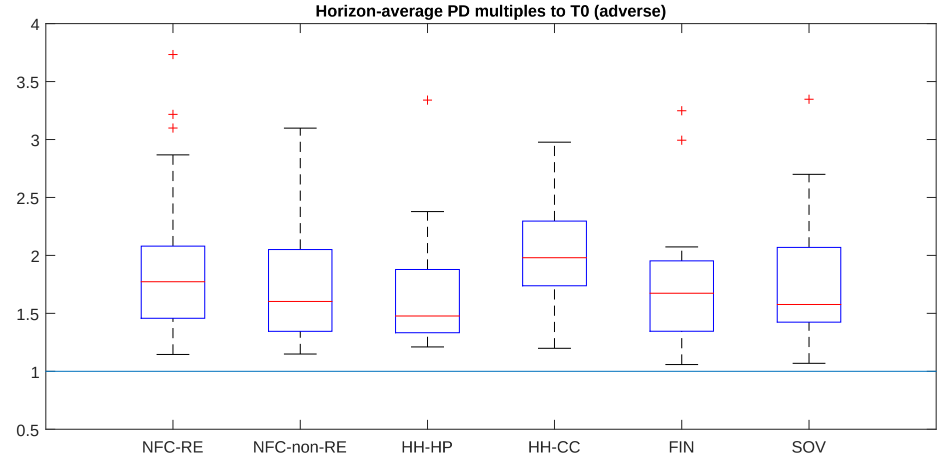
Chart 4.3 shows the cross-country distributions of "PD multiples" relative to the PD starting points at the respective country and segment levels. The underlying PD projections reflect the scenario-conditional forecasts from the PD satellite model suite for the 28 EU countries and the six portfolio segments. The PD multiple is defined as the average ratio of projected PD levels along a three-year scenario horizon over the starting point PD. The projections are conditional on an illustrative multi-country adverse scenario which is similar to that of the EBA Stress Test 2016.[42]

42 See http://www.eba.europa.eu/documents/10180/1383302/2016+EU-wide+stress+test-Adverse+macro-financial+scenario.pdf

Chart 4.3

PD multiples under an adverse scenario

(multiples)

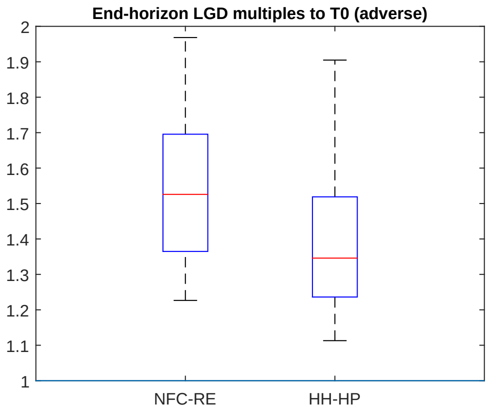


Notes: The multiples represent horizon averages of three multiples corresponding to three years relative to a T0 starting point. The red lines indicate the median; the upper and lower edges of the boxes mark the 75th and 25th percentiles of the cross-country distributions; the whiskers extend to the data points farthest out of the distributions that are not considered outliers yet. The red crosses mark the ‘outliers’, though these are not considered outliers in the sense that they are not economically meaningful and requiring revision; only in a statistical sense they are detected as being farther away from the centre of the distribution.

Chart 4.4

LGD multiples under an adverse scenario

(multiples)



Notes: The multiples are the factor by which starting point LGDs are to be multiplied to arrive at adverse LGD levels by the end of a three-year scenario horizon. The intermediate year LGD multiples distributions tend to fall between 1 and the distribution shown for the third year as long as house price declines under an adverse scenario are assumed to be gradual along the horizon.

With regard to the LGD model and its implied parameters, Chart 4.4 shows the corresponding illustrative results. As outlined above, the LGD multiples are a function of only the house price movements in the scenario, that is, the commercial and residential property price scenario profiles, respectively, are used to translate into NFC-RE and household mortgage-related LGD forward paths.

4 Conclusions

The purpose of this chapter was to present the credit risk modelling framework, in particular concerning the projection of PD and LGD parameters conditional on some macro-financial scenarios. The PD satellite models have been developed using a Bayesian model averaging framework, while the LGD model is a more structural model that does not require any historical LGD data.

The credit risk models, beyond providing quality assurance inputs for system-wide microprudential exercises such as EBA, form an integral part of the modelling toolkit employed by ECB staff for macroprudential purposes. With a view to the latter, the models are used to assess the impact of the materialisation of risks in the financial sector on the credit risk parameters. The implied loan losses are a major channel through which the solvency position of European banks is affected by stress arising from macroeconomic shocks, which warrants a detailed quantification. The models that have been documented in this chapter are therefore an important building block for any macroprudential application of the ECB staff top-down stress test toolkit.

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Chapter 5 Satellite models for bank interest rates and net interest margins

By Marco Gross, Björn Hilberg, and Cosimo Pancaro

Banks' core activities consist in the acceptance of deposits and the creation of loans. Thus, their balance sheets, to a large extent, comprise interest-bearing assets and interest expense-generating liabilities. Consequently, changes in interest paid or received are among the most material sources of variation affecting a bank's profits and losses and hence its solvency position. Therefore, the satellite models that address interest rate risk (along with the credit risk models, see Chapter 4) play an essential role in the overall stress test toolkit used for macroprudential assessment purposes.

ECB staff have employed two complementary modelling approaches to translate macro-financial scenarios into developments in banks' net interest income, both being presented in this chapter.

The first approach, presented in Section 1, uses country-level data on front-book interest rates, i.e. rates on new business, which are available as an input for different asset and liability segments. The satellite models provide, as an output, the country and segment-specific projections of front-book interest rates conditional on a given macro-financial scenario. These paths, once combined with the scenario-conditional evolution of gross and performing loan stocks (see Chapter 9), imply an interest income and expense flow which, in turn, can be expressed in the form of a net interest margin (NIM), i.e. the ratio of net interest income over interest-bearing assets and a key driver of banks' profitability.

The second modelling strategy, presented in Section 2, relies on a dynamic panel approach to directly estimate the relationship between banks' NIM and a set of selected macro-financial variables, applying a variable-selection technique. The estimated model parameters are then used to project banks' NIM conditional on a given macro-financial scenario. This approach is less demanding in terms of the required data inputs and is suitable for macroeconomic analyses. In addition, the first approach is also suitable for quality assurance in the context of supervisory stress tests owing to the more granular data inputs required.

1 Satellite models for bank interest rates

This section presents the satellite models for interest rate spreads of eight portfolio segments, as well as a summary of the approach employed for the remainder of the portfolio segments for which satellite models are not available (due, for example, to missing historical data series for some countries and segments). The satellite models capture the pass-through of market funding conditions to both the funding cost components of the banks on their liability side and the pass-through to the loan interest rates on their asset side. Importantly, the satellite equations that will be presented also allow macro-financial variables to appear, next to market interest rates, as predictor variables. This is meant to reflect the fact that spreads of bank lending rates over reference rates reflect macroeconomic conditions in general, and, related to that, the risk of the borrowers in particular. Bank-specific interest rate spreads for all relevant portfolios are projected at the country level based on the satellite model system and are attached to the banks' own starting points to eventually derive the banks' net interest income.

1.1 Data

As a basis for the interest rate models and projections, front-book interest rates, i.e. rates on new business, relating to loans and deposits are taken from the ECB's monetary financial institutions interest rate (MIR) statistics. Interest rates on new loans are available for loans to non-financial corporations, mortgage loans and consumer credit across the 28 EU countries. Loans to non-financial corporations with an original loan amount of more than €1 million are used as a proxy for loans to large corporates. Similarly, loans to non-financial corporations with an original loan amount of less than €1 million are defined as loans to small and medium-sized enterprises. In addition, data on new sight and term deposits from households and non-financial corporations are used.

Interest rates can be split into a spread and a reference rate component to distinguish two risks affecting banks' net interest income under stress. The earnings risk related to a change in the general "risk-free" yield curves is captured by changes in the reference rate component of banks' assets and liabilities. The earnings risk related to a change in the spread that the market requires, or which the bank sets for different types of instruments, reflects changes in credit risk and other market risks. Front-book interest rate spreads can be constructed by subtracting swap rate levels from front-book interest rates. There are two options for choosing an appropriate swap rate. A first option is to refer to a correlation measure of front-book rates and swap rates for different currencies and maturities. The swap rate maturity that correlates most closely with a front-book interest rate could then be chosen to compute the spread. Alternatively, if information on the average maturity of a given portfolio is available, another option is to choose for the relevant portfolio currency the swap rate that is closest in terms of its maturity to the average portfolio maturity.

The resulting country-level spread series are the basis for the subsequent econometric modelling step, whereby a link to macro-financial predictor variables is established, making it possible to derive the interest rate spread and level projections for all the relevant asset/liability classes. The interest rate spreads to swaps and corresponding models are developed for each country and segment, at least for its "main" country-currency pair (for selected countries where loan exposures in a second currency are significant, additional satellite models are developed for the same country).

1.2 Model structure

As for credit risk in Chapter 4 and various other satellite model components of the stress test toolkit, Bayesian model averaging (BMA) technique is employed for modelling and projecting front-book interest rate spreads at the individual country and portfolio levels.[43] The basis for the BMA methodology for the interest rate spreads can be represented as an autoregressive distributed lag (ADL) model structure:

$$i_t - ref_t \equiv s_t = \alpha + \rho s_{t-1} + \cdots + \beta_1 ref_t + \cdots + \beta_q ref_{t-q} + \sum_{g=1}^{G} \left(\gamma_g X_t^g + \cdots\right) + \varepsilon_t$$

The front-book interest rate spread is allowed to be a function of its lags, the reference rate, the additional potential predictors and lags thereof. Importantly, in addition to the potential predictors X_t, the reference rate (swap rate or short-term money market interest rate) variable at the respective maturity that was employed to compute the spread was also allowed to enter on the right hand-side of the model. By doing so, the effective pass-through of the reference (swap) rate is allowed to be different from 1.

The list of potential macro-financial factors, including the reference rate, along with the sign restrictions imposed on the long-run effects of the predictor variables, is shown in Table 5.1 for all portfolio segments.

Table 5.1

Predictor inclusion settings and sign constraints

		Real GDP	Real private consumption	Real investment	Real exports	Unemployment rates	Consumer prices	Residential property prices	Swap rates	Sovereign bond yield spread	Short-term interest rate
Asset side	L-CORP-LARGE	0		0	0		0		0	0	0
	L-CORP-SME	0		0	0		0		0	0	0
	L-HH-HP	0	0			0	0	0	0	0	0
	L-HH-CC	0	0			0	0		0	0	0
Liability side	D-CORP-SI	0		0			0		0	1	1
	D-CORP-TE	0		0			0		0	1	1
	D-HH-SI	0	0				0		0	1	1
	D-HH-TE	0	0				0		0	1	1

Notes: L-CORP-LARGE - loans to large non-financial corporations, L-CORP-SME - loans to small- and medium-sized enterprises, L-HH-HP - loans to households for house purchases, L-HH-CC - consumer credits, D –CORP-SI - sight deposits from non-financial corporations, D-CORP-TE - term deposits from non-financial corporations, D-HH-SI – sight deposits from households, D-HH-TE – term deposits from households

A “1”, “0” or “-1” means that the respective predictor variables were allowed to appear, respectively, with a positive sign, without any sign restriction or with a negative sign (no “-1” in fact is given in the table). Where no entry in the table means that a variable was excluded a priori. Rather few sign constraints need to be imposed on most of the potential predictors in Table 5.1. The reason being that in the vast majority of posterior models across countries and segments, the signs of the long-run multipliers are in fact in line with prior expectations. The positive sign

[43] See Gross and Población (2017) for details concerning the econometric model methodology.

constraints on the sovereign bond yield spreads and the short-term money market rates on the liability side can be imposed, to stress deposit rates.

The list of predictor variables is different for corporate loans and loans to households. For interest rate spreads on corporate loans GDP, investment and export growth, consumer price inflation, sovereign bond yield spreads to Germany, and short-term money market rates are included. Interest spreads for retail loans are allowed to relate to GDP growth, private consumption growth, unemployment rates, house prices (for mortgages only), and to sovereign bond yield spreads to Germany, as well as short-term money market rates.

Similar to the asset side, the list of potential predictor variables is different for corporate deposits and deposits from households. Corporate deposit rates are allowed to react to investment growth but not to private consumption growth and vice versa for deposits from households. Moreover, in contrast to loans, deposit rates are restricted to react in the same direction as sovereign bond yield spreads to Germany and short-term money market rates.

Once estimated for the various segments and across countries, the models can be used to produce point and density forecasts of all front-book spreads conditional on some macro-financial scenario. The density forecasts and the chosen percentiles reflect three sources of uncertainty: model uncertainty, coefficient uncertainty and residual shock uncertainty, as for PDs (see Chapter 4). An option in this case is to employ non-median percentiles of the resulting conditional density. For the asset side, this approach implies choosing a percentile below the median. For the liability side, instead, this requires selecting percentiles above the median. In terms of screening principles and acceptance criteria, the approach defined for the interest rate spread model review is also very similar to the one for the credit risk satellite models.

In addition to the sign constraints imposed at the BMA modelling stage, additional restrictions can be imposed *ex post* on the path of the front-book rate spreads separately for each individual country-currency pair. For instance, a restriction can be imposed, to the extent to which the interest rate on the asset side is allowed to increase relative to a reference rate.

$$\Delta s_{t,i,j} = min\left(\Delta s_{t,i,j}, \max(0, \lambda \times \Delta ref.rate_t)\right)$$

Where $s_{t,i,j}$ is the projected change in the front-book interest rate spread of an asset *i* in country *j* at time *i*, $\Delta ref.rate_t$ is the change in reference rate of choice, and λ is a scaling factor which allows for a pass-through of the change in the reference rate which is different from one.

1.3 Approaches for countries/segments without data and/or models

For a number of countries and portfolio segments, the historical time series of front-book rates are either not available or of insufficient quality or time series length. The approach that is employed to address and solve that issue differs for EU and non-EU countries.

The cross-filling approach, as presented earlier for credit risk parameters (see Chapter 4), is employed again for all countries/currencies and portfolio segments for which no satellite model could be developed. In such a case, the translation of the scenario for a missing country and segment is derived from the models available for all other countries in the same segment.

For non-EU country-currency pairs, there is no data source comparable with the MIR statistics that would contain detailed portfolio-level interest rates on new business. Hence, for non EU country-currency pairs, a rule-based calibration is employed. For the asset side, bank interest rate spreads are assumed to stay constant. For the liability side, under an adverse scenario, bank interest rate spread paths are linked to the change in the bond yield spread of the sovereign corresponding to the country. For each segment, the pass-through of this change is calibrated based on a cross-country regression:

$$s_{t,i,j} = \alpha + \beta\, ref.rate_{t,i,j} + \gamma\, sov_{t,j} + \varepsilon_t$$

Where $s_{t,i,j}$ denotes the front-book interest rate spread of asset *i* in country *j* at time *t*, $ref.rate_{t,i,j}$ is the change in selected reference rate of asset *i* in country *j* at time *t*, and $sov_{t,j}$is the sovereign bond yield of country *j* at time *t.*

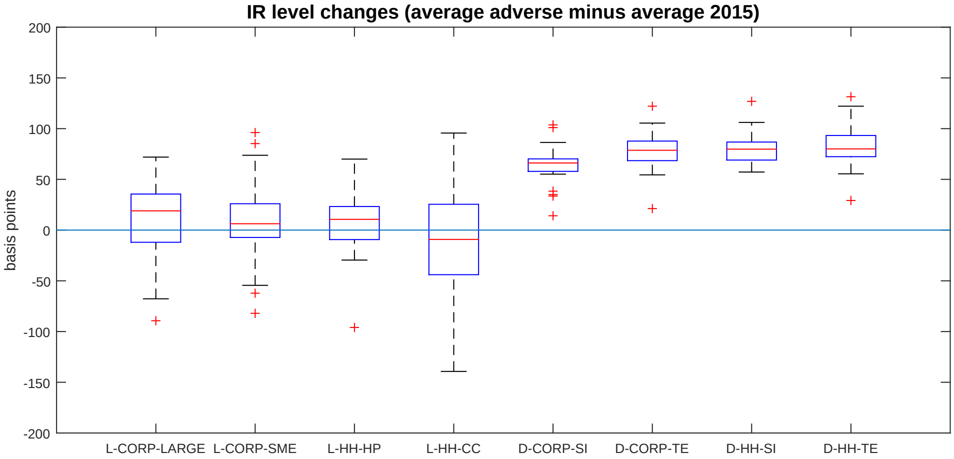
1.4 Illustrative scenario-conditional forecasts for bank interest rates

Chart 5.1 shows a collection of box plots that visualise illustrative projections of front-book rate levels which are based on adverse scenario assumptions similar to those of the Stress Test 2016. Box plots are shown for the eight segments and are based on the average level change (relative to the starting point) from along a three-year scenario horizon. The distribution reflects the scenario paths of all 28 EU countries.

Chart 5.1

Bank interest rate level changes under an adverse scenario

(basis points)



Notes: L-CORP-LARGE: loans to large non-financial corporations, L-CORP-SME: loans to small and medium-sized enterprises, L-HH-HP: loans to households for house purchases, L-HH-CC: consumer credits, D–CORP-SI: sight deposits from non-financial corporations, D-CORP-TE: term deposits from non-financial corporations, D-HH-SI: sight deposits from households, D-HH-TE: term deposits from households. The red line denotes the median and the upper and lower bound of the box represent the interquartile range between the 25th and 75th percentile. The red pluses identify possible outliers based on the observed interquartile range.

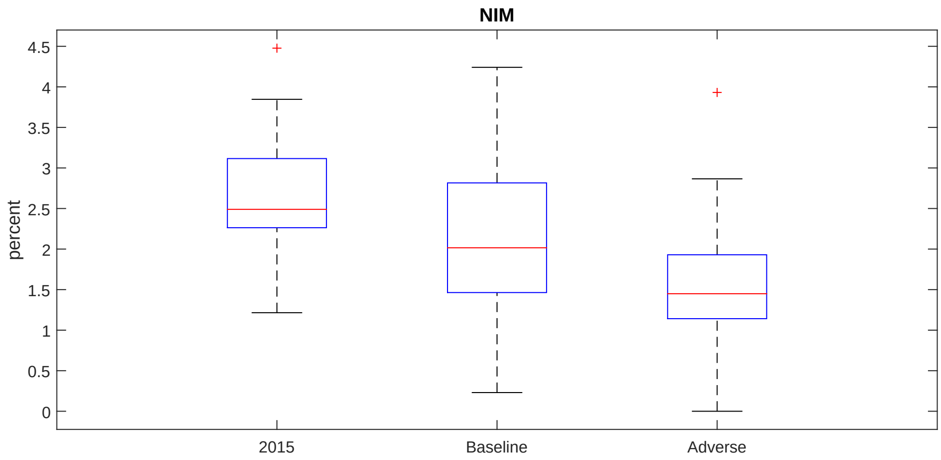
The new business interest rate level changes, as depicted in Chart 5.1, are then applied to individual banks' interest rate starting points to obtain bank, segment and country-specific interest rate paths. In addition, bank-level information on the new business volumes is required (see Chapter 9 for the corresponding models). Moreover, the projected paths of expected default rates resulting from the credit risk models (see Chapter 4) determine the portion of the gross loan stock that is performing and therefore generating income in a given period. The business volume which does not mature in a given period is not repriced and continues to earn the same interest rate. By applying these new business interest rate projections to the banks' new business volumes on the asset and liability side, in conjunction with the information on the interest rates and volumes of the loan stocks which are not re-priced over the projection horizon, one obtains a projection of the banks' interest income and expenses, and hence a path for net interest income. At this point, the calculation of the interest income and expense streams involves some additional information about repricing frequencies and average original maturities at bank/portfolio level, which is necessary in order to distinguish between new business and variable, as opposed to fixed rate, existing business.

Based on the projected trends in front-book rates of assets and liabilities, Chart 5.2 shows the distributions of the NIM under the baseline and adverse scenarios, on average, over the scenario horizon, along with a starting point distribution (referred to as 2015 in the chart). The NIM is implied here by the projections for loan and deposit rates, which distinguishes this model approach from the one that is presented in the next section, which uses the NIM directly as a dependent variable.

Chart 5.2

Developments in net interest margin (NIM) evolution implied by front-book interest rate projections

(percentage)



Notes: The NIM is defined as the ratio of net interest income over the sum of interest-bearing assets. The underlying country-level NIM estimates are a function of the changes in new business interest rates under the scenarios along with various additional assumptions concerning the repricing frequency and maturity profile developments for loan stocks.

2 Satellite models for banks' net interest margin

This section presents an alternative panel-based modelling strategy that can be employed to derive top-down projections for the NIM conditional on baseline and adverse macroeconomic scenarios.

2.1 Data

This approach uses an unbalanced panel of annual data from 1991 to 2014 for a sample of euro area banks established in the 19 euro area countries. The coverage of banks in the sample tends to increase over time, i.e. the most recent years typically have the best coverage. The banking data were extracted from Bloomberg.

The dataset used in this analysis includes 111 banks. The most-represented countries are Germany (21 banks), Spain (15), Italy (15) and France (11). Cyprus, Estonia, Luxembourg, Lithuania and Malta each have only two banking institutions in the sample.

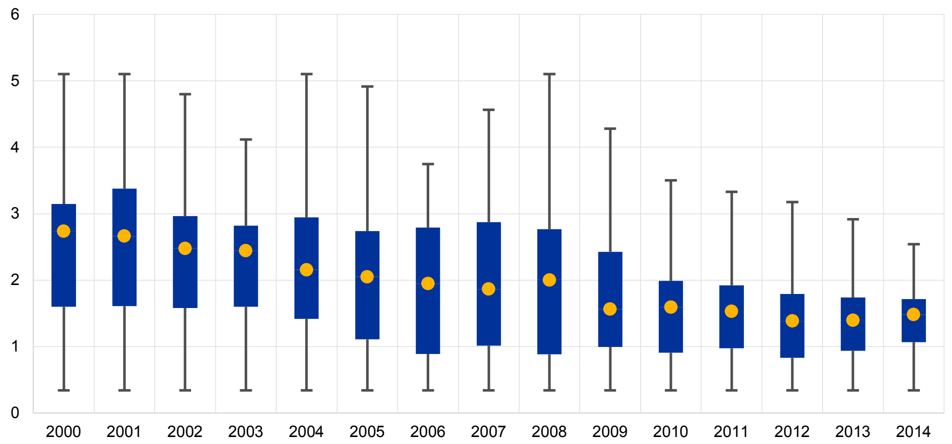
The dataset also includes a series of potential explanatory macroeconomic and financial variables for the euro area countries. This set of variables has been selected in line with the literature (e.g. Albertazzi and Gambacorta (2009), Covas, Rump and Zakrajšek (2014), Busch and Memmel (2015)) and is also limited to variables that are available in standard macroeconomic stress scenarios. These explanatory variables are both the contemporaneous value and the first lag of each of the following: the short interest rate, the slope of the yield curve defined as the spread between the long-term and the short-term interest rates, the real GDP growth, the HICP annual inflation rate and credit growth. The macroeconomic and financial variables were extracted from the ECB Statistical Data Warehouse.

2.2 Some stylised facts

In the last few years, increasingly strong competition in traditional banking activities and a fall in interest income due to the low interest rate environment have increased the pressure on euro area banks' NIM. Indeed, between 2000 and 2014 the median NIM for the sample of euro area banks under consideration halved, from 3% to about 1.5% (Chart 5.3). At the same time, the median ratio of net interest income to net revenue[44] (Chart 5.4) for the same sample of banks has not declined and hovered around 60% over the last 14 years. As expected, this indicates that net interest income remains the main source of income for euro area banks. However, the trend in the median net interest income (both over assets and net revenue) shows considerable heterogeneity across euro area countries.

Chart 5.3
Net interest margin

(percentage, 2000-14)



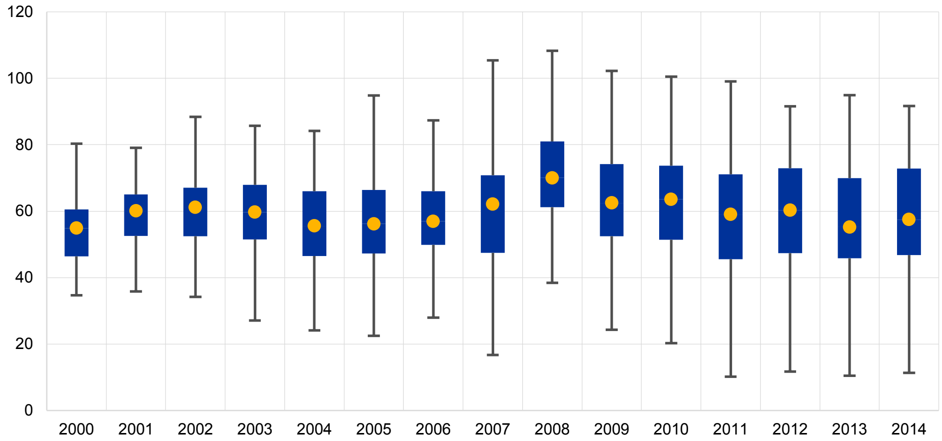
Sources: Bloomberg and authors calculations.

44 Net revenue is the sum of interest income, trading account profits (losses), investment income (losses), commission and fees earned and other operating income, minus interest expense.

Chart 5.4

Net interest income over net revenue

(percentage, 2000-14)



Sources: Bloomberg and authors calculations.

2.3 Variable selection: least angle regression procedure

There is a rather large set of factors that may be associated with developments in the NIM. In order to examine which variables influence the dependent variable the most, a variable selection procedure is applied. Indeed, in the presence of many candidate variables, the objective is to choose as regressors those variables that have the most explanatory power for the variable of interest, while keeping the model relatively sparse to avoid over-fitting. For the purpose of variable selection, the least angle regression (LARS) algorithm (developed by Efron and Tibshirani, 2004) is employed.[45]

In this analysis, the initial set of variables to which the LARS algorithm is applied comprises the lagged NIM, the short-term interest rate, the slope of the yield curve[46], the real GDP growth, the HICP annual inflation rate, credit growth and the lags of each of these macroeconomic and financial variables. This set of variables is determined based on economic rationale and the related empirical literature, and includes only macroeconomic factors typically covered by stress test scenario assumptions.

45 The LARS algorithm can be seen as a generalisation of the least absolute shrinkage and selection operator (LASSO) by Tibshirani (1996) and the forward stagewise linear regression (Stagewise). The LARS approach, which derives its name from the underlying geometry, is a stepwise shrinkage and selection procedure that starts with all coefficients at zero and then moves with equiangular movements towards a predictor variable which is as highly correlated with the residual as the other variables already used in the prediction. To perform variable selection, Efron and Tibshirani (2004) suggest making use of Mallow's Cp statistic, a standard information criterion, which is often used as a stopping rule in a model selection context.

46 The slope of the yield curve is defined as the spread between the ten-year sovereign rate and the three-month money market rate.

Table 5.2 shows the results from the variable selection procedure. More specifically, it provides the order of inclusion of each variable, statistics at each step for the resulting model and the R-square implied by the individual models. Efron and Tibshirani (2004) suggest selecting the set of variables as implied by the minimum value of the Cp statistic. The model implied by the minimum Cp statistic includes seven variables (including the constant). The variable set selected by the LARS approach comprises, in decreasing order: the lagged NIM, the short-term interest rate, the lagged and contemporaneous real GDP growth and the lagged and contemporaneous slope of the yield curve.

Table 5.2

LARS: selection of variables included in the model

Step	Cp	R-square	Variable added
1	8,909.80	0.00	
2	58.36	0.8803	Net interest margin (t-1)
3	54.25	0.8809	Short-term interest rate
4	31.50	0.8833	GDP growth (t-1)
5	19.64	0.8847	GDP growth
6	16.93	0.8852	Spread (t-1)
7	15.46*	0.8855	Spread
8	16.24	0.8856	Inflation rate (t-1)
9	16.43	0.8858	Inflation rate
10	16.51	0.8860	Credit growth (t-1)
11	17.03	0.8868	Short-term interest rate (t-1)
12	17.31	0.8869	Credit growth

Source: authors calculations.
Notes: The table shows results based on the LARS variable selection algorithm. At each step of the procedure, the Cp statistic, the R-squared of the model and the newly included variable is provided. The model with the minimum Cp value is marked with an *.

2.4 Econometric framework

The cyclical dynamics of the NIM are, in a second step, modelled using a panel data econometric framework. In particular, as shown in Equation (1), a dynamic modelling approach is adopted in order to account for the potential time persistence of the NIM:

$$y_{it} = \mu_i + \alpha y_{it-1} + \beta X_{it} + \varepsilon_{it} \qquad (1)$$

Where, y_{it} is the NIM for bank i and period t, y_{it-1} is the lagged dependent variable, X_{it} is the vector of explanatory variables identified by the application of the LARS methodology, μ_i is a bank fixed effect and ε_{it} is an idiosyncratic shock. Because the inclusion of the lagged dependent variable might yield biased and inconsistent estimates owing to the correlation between the lagged dependent variable and the error terms, Equation (1) is estimated using a system- generalised methods of moment (GMM) estimator[47] (Blundell and Bond 1998)[48].

[47] Specifically, a one-step estimation approach with robust standard errors is applied.

The estimates show that the signs of the estimated coefficients are as expected and in line with the previous literature when significant. The variables which are significantly related to the NIM are the lagged dependent variable, the short-term interest rate, the lagged real GDP growth and the lagged spread.

The regression analysis finds that the estimated coefficient of the lagged dependent variable has a positive sign. This suggests the persistence of NIM over time.

The results also indicate that the NIM is positively related to both the level of short-term interest rates and to the lagged slope of the yield curve. These results can be attributed to the two key services supplied by banks, which are also reflected in their interest income earnings; specifically, maturity transformation and deposit transaction services. The slope of the yield curve result reflects the return to banks from maturity transformation. The short-term interest rate result reflects the fact that bank deposit rates are typically lower and stickier than market rates (since banks provide transaction services). In particular, banks often fund a portion of their interest-earning assets with non-interest-bearing liabilities which primarily correspond to demand and transaction deposits. Therefore, a shift of the interest rates primarily affects the income side and, thus, leads to a change in the net interest income.

Finally, the results show that the NIM is positively related to the dynamics of the macroeconomy via the lagged real GDP growth. Indeed, improving macroeconomic conditions should lead to an increase in credit demand and supply and thus an expansion of banks' interest-earning opportunities.[49]

Table 5.3

Net interest margin: regression results

Variable	Coefficient
Net interest margin (t-1)	0.849***
Short-term interest rate	0.043**
Real GDP growth (t-1)	0.021***
Real GDP growth	0.005
Spread (t-1)	0.032***
Spread	0.007
Number of obs.	1,153
Diagnostic statistics	
AR(2) Arellano-Bond test (p-value)	0.835
Hansen J test (p-value)	0.295

Source: authors calculations.
Note: ***, ** and * denote significance at the 1%, 5% and 10% level respectively.

[48] The inclusion of a lagged dependent variable in a panel framework might yield biased and inconsistent estimates owing to the correlation between the lagged dependent variables and the error terms. This is referred to as dynamic panel bias (see Nickell (1981) and Kiviet (1995)).

[49] The Arellano-Bond test does not reject the null hypothesis of the absence of second-order autocorrelation in the estimated residual. The Hansen test does not reject the hypothesis that the instruments are valid (i.e. that the instruments are uncorrelated with the error term).

2.5 Scenario-conditional forecasts for bank net interest margins

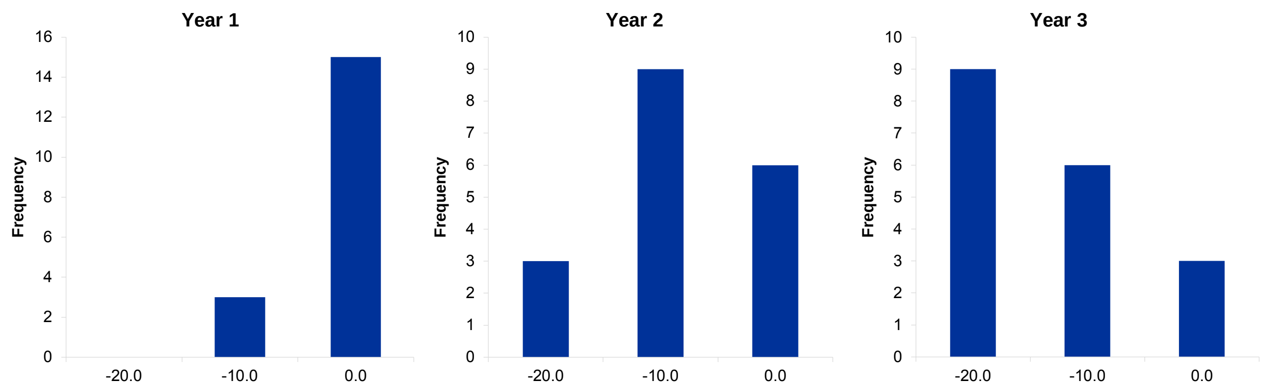
The estimated parameters in Table 5.2 can then be used to project the NIM conditional on baseline and adverse scenarios. The bank-specific NIM projections are computed year by year along the scenario horizon and then aggregated at the country level as a weighted average of the individual banks, using the respective shares in the countries' total assets.

For illustrative purposes, the EBA 2016 scenarios have been used in what follows. The NIM projections (reported in Chart 5.5 as changes with respect to cut-off levels) are sensitive to the different macroeconomic scenario assumptions. As expected, the projections are consistently less favourable under the adverse scenario than under the baseline scenario. Overall, the adverse scenario produces its strongest impact in the third year of the stress test horizon. In the first year the NIM drops by less than 10% for the majority of the countries.[50] In the second year the NIM falls by between 10% and 20% for nine countries and by more than 20% for three countries. Finally, in the third year the projected NIM drops by more than 20% for nine countries and by between 10% and 20% for three countries.

Chart 5.5

Distribution of NIM projections at the country level under the adverse scenario, by stress test year

(percentage, change with respect to the cut-off level)



Source: authors calculations.

3 Conclusion

This chapter presented two modelling approaches that can complementarily be used to derive scenario-conditional forecasts for banks' net interest income and to assess the resilience of banks' net interest income to a given stress scenario.

The first modelling strategy using sectoral data employs an ADL model structure together with a BMA methodology and sign restrictions to obtain new business

[50] The variations in the NIM over the stress test horizon described in this section are expressed as changes with respect to cut-off levels.

interest rate models at the country and portfolio levels. These models are used to derive scenario-conditional paths for banks' interest rates, which are then combined with either bank-level or country-level interest rate level starting points to obtain bank or country-specific interest rate paths for new business. By applying these to new business volumes on the asset and liability side and combining it with the information on the interest rates and volumes of the loan stock, one obtains a projection of the banks' interest income and expenses, and hence a forward path for net interest income conditional on a macro-financial scenario.

The second modelling strategy using panel data employs a variable-selection technique to determine the set of relevant regressors for the NIM. Then it uses a dynamic panel model to estimate the relationship between the NIM and a selected set of economic and financial variables. Using the estimated model parameters, banks NIM can be projected conditional on both a baseline and an adverse macro-financial scenario.

The bank interest rates model system assumes an important role in the overall stress test toolkit (along with the credit risk models, see Chapter 4) because interest rates and credit risk are the most material sources of variation affecting a bank's profits and losses, and hence the capital position of banks. Both approaches allow estimates of the impact of macro-financial shocks on interest income and interest expenditures to be obtained either by assessing the impact individually for each portfolio of a bank or at the level of the net interest margin. The results of such models are a valuable input into the analysis of banks' profitability under a wide range of relevant macro-financial scenarios as well as in a macroprudential application of the stress test toolkit.

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Chapter 6 Top-down modelling for market risk

By Dimitrios Laliotis and Will Mehta

This chapter reviews the ECB staff approach to market risk top-down (MRTD) modelling. Market risks (MR) have in the past been challenging to model, specifically credit counterparty risk (CCR), counterparty valuation adjustment (CVA), held for trading (HFT) and market liquidity (ML). The chapter looks at the specific challenges encountered in building these models and discusses the options available to address them. It also goes on to assess the benefits of and drawbacks to the available modelling choices.

An overview is provided of the model methodology and data used, looking at the common elements across the models.

The chapter then reviews each of the models, looking at deviations from the standard methodology used in modelling and examining the performance of the models against the banks' own results. The models can be used in a macroprudential top-down (TD) stress test. While MR is not the highest impact risk in the euro area it can have a sizable adverse effect and tends to have a greater impact on the larger, more systemic banks. Finally, there is a brief discussion of the potential uses of the models in the context of assessing market risk for euro area banks.

1 Introduction

TD modelling for market risk has been one of the least-explored areas of TD modelling. There are a number of reasons for this. In the euro area, MR is one of the smaller risks (in relative terms) that banks face. In the 2016 EBA stress tests, the impact of market risk on CET1 across the banks was 100 basis points, about a quarter of the impact of credit risk. Furthermore, the bulk of the losses in MR are attributed to stressing the Available For Sale/Fair Value Option (AFS/FVO) portfolios (the various risk types are described below), the modelling of which has already received substantial attention. Nonetheless, MR can be significant in stress testing. Certain scenarios may emphasise it more (such as a sharp yield reversal) and it has a greater impact on the larger banks. MR is a broad term that covers losses from positions that are marked to market for accounting purposes. The positions in MR stress testing are defined by all positions in the HFT, AFS and fair value option (FVO) accounting classifications.

From a regulatory classification perspective, MR is less straightforward, not least because it involves positions in both the trading book and the banking book that use these accounting classifications.

MR stress testing involves calculating the losses that would arise from these positions in a stressed environment. Given the complexity of some of the positions, this entails looking at a number of risks that these positions face. The EBA methodology breaks these risks down into the following:

- Held for trading (HFT)
- Available for sale/fair value option (AFS/FVO)
- Counterparty credit risk (CCR)
- Jump to default (JTD)
- Counterparty valuation adjustment (CVA)
- Market liquidity (ML)
- Risk exposure amounts (REAs) related to market risk (MR)

Before giving more details on the individual risks, it is worth noting at the outset that one specific position can be affected by a number of the above risks.

HFT/AFS and FVO – these two relate to the same risk but are for the positions in the particular accounting regime. Both relate to the risk of loss due to movements in the price of securities and derivatives. If a bank holds an equity position, it risks a loss because of the fall in the price of the equity. Broadly, for this risk, banks use the stress scenario, which provides the projected change in the prices in the scenario, to revalue their portfolio. This revaluation usually results in a loss for the bank (although in some circumstances it can be a profit, e.g. if the bank holds a short position in an equity and that equity price falls).

CCR – this risk applies to derivatives across all the MR accounting classifications. It is the risk that a counterparty to a derivative defaults and therefore cannot make the (full) payments due on the derivatives it has contracted. In a supervisory stress test, the methodology will generally detail how many counterparties are to default and how to choose the counterparties that will default in the scenario.

JDT – this is the equivalent risk to credit counterparty for securities. It is the risk of loss due to the default of an issuer of a security, meaning that the issuer is unable to make the (full) payments relating to the security.

CVA – this is the adjustment made to the price of a derivative to take account of the creditworthiness of the counterparty to the derivative. In the stress scenario, the creditworthiness will change (as will the expected cash flows on the derivative), triggering the need to revalue the CVA. Banks do this by revaluing the CVA using the prices from the stress scenario. In this sense, it is very similar to HFT. In fact, it is part of the revaluation of the derivatives in a stress scenario; it is normally split out from HFT simply because of its complexity.

ML – this is part of HFT, but is mentioned in isolation because a separate model can be built for it. This is because it has very different drivers from the rest of HFT. It is the risk of loss due to the widening of the bid/offer on a position. HFT takes account of all the movement in the price of positions, but these can be broken down into the move in the mid-price of a position and the widening of the bid/offer spread. This latter element is the market liquidity risk.

REAs – this is the risk that REAs for MR increase under the stress scenario, leading to an increase in the bank's overall capital requirement.

2 Data

Before looking at the models, the data set that was used for most of the models needs to be described, as it is substantially different from other TD models.

For instance, for credit losses (see Chapter 4), probabilities of default (PD) are modelled. For data, the modelling uses a series of PDs over time. There are many challenges in obtaining and using these data but, at its core, it is a relatively simple process. These PDs (together with the loss given default, or LGD) can then be applied to a bank's current credit exposures to produce the stress losses. There is no obvious equivalent to PDs for any of the risks in market risk, even counterparty risk (as discussed later). To try to think about MR in a similar manner, one could try to produce an equivalent to credit exposures and then consider an equivalent to the combination of PDs and LGDs, with overall losses being equal to exposures multiplied by this parameter. At the same time, what is available is only the combination of all three of these, that is, the overall losses that come from MR. If there were an equivalent of risk exposure for MR, one could divide the losses by the metric to produce the equivalent of PDs and LGDs combined, which would make it possible to model these data.

There are difficulties, however, with modelling both losses and risk exposure for MR.

Starting with exposures, one crude but simple measure would be the notional of the portfolio. The notional is the metric used to define the contractual size or nominal amount of derivatives. If one purchased an equity option, it would be the right to buy (or sell) a certain number of shares. To make notionals comparable across asset classes, the metric is used in the form of a euro amount. In the case of the equity option, this would be the number of shares multiplied by the price of those shares. For an interest rate swap, the notional is the amount to which the fixed and floating rates are applied. With a fixed for floating swap, one would specify an amount to which those rates should be applied in calculating the payments due on the swap. The notional can be used for all derivatives asset classes.

While the notional does then provide a metric for the size of a derivatives portfolio, it is not a very risk-sensitive measure. Two derivatives with exactly the same notional can indeed have very different reactions in a stress test. Consider, for example, two "vanilla" options with the same notional. One is "at the money" before the stress scenario (that is, its strike is equal to the current level of the underlying to the option) and the other is a deeply "out of the money" option (that is, an option with a strike a long way from the current underlying which will pay nothing if the underlying stays at this level). These will react very differently to a stress scenario, even if their notional is exactly the same because the at the money option is more sensitive to moves in spot than the out of the money option (this dynamic can change depending upon the size of the move in the underlying and the distance of the strike from the pre-stress underlying price, making the reactions of the two options very sensitive to the scenario). Even more extreme examples are available if one considers exotic options; these often provide multiples of a vanilla pay-out and therefore react very differently in a stress test.

There are other potential measures for exposure. One would be risk sensitivities. These provide the loss a portfolio would suffer for a small move in various market risk factors (such as a small move in the Eurostoxx or in the five-year euro swap rate). These have the drawback of being local sensitivities, that is, they are only relevant for small but not large moves. They do not, therefore, capture some of the non-linearities that may exist in the portfolios. They do have the advantage of being clearly defined and used widely across banks.

Finally, there are more complex metrics such as Value at Risk (VaR), a measure of HFT risk. It can be thought of as the worst of a series of stress tests. There are, however, a number of potentially serious issues with VaR. It is not well defined, and hence bank dependent, and purely probabilistic.

These three examples provide some detail about the challenges in choosing an appropriate metric for market risk. At one end of the spectrum of choices, there are simple metrics which are the same across banks, but which do not capture the potential idiosyncrasies in product reactions to a stress test. At the other end of the spectrum, there are more risk-sensitive measures that are complex to calculate and use, and are less comparable across banks.

There are additional challenges with the loss data. It is also very difficult – practically impossible – to dis-aggregate the losses in MR from net trading income (NTI) and separate them into the individual risk types that make up the full MR approach.

In financial accounts, banks report net trading income. This number is made up of a few constituents. It includes revenue that the banks make during the course of trading. This revenue itself includes gains or losses on positions held but also contains revenue that is more like commission. This revenue is generated from buying and selling a position, instantaneously contracting as principal. It contains losses incurred due to the revaluation of CVA and bid/offer spreads. It is not possible to split out these losses using information available from a top-down perspective. Having disaggregated information would be crucial to the TD modelling for MR. While it would be possible to model MR together with NTI as one large group, such an approach would not allow for the riskiness of individual risks in the methodology to be realigned and would thereby severely limit the potential range of methodologies available for a stress test. From a macroprudential perspective, this would limit the range of issues that could be explored through a stress test (these are discussed later in the chapter). More fundamentally, it would make it impossible to consider the riskiness of different MR risks separately. At a time of significant change to both regulation and business models, this type of modelling would simply be too broad.

There are other problems, too, for modelling losses which could be highly significant, some of which will be familiar to credit risk modellers. Any historical time series for CVA is likely to be short. Many banks did not start accounting for CVA until after the 2008 crisis. More generally, MR has gone through very significant changes in the past few years, driven by profitability issues and regulatory change. While CVA is likely to be the most clear-cut case, all risks will be significantly affected by time series, where the older observations could be poor indicators of the future.

The counterparties that are most relevant to CCR are large banking groups. The history of defaults of large banks with significant MR activity (and therefore exposure) is limited. In any time series, Lehman's would likely be the only event. As such, modelling using historical data could be difficult. It would be possible to use PDs either from models or implied from the market and this is an area of potential future research. It would still need to be combined with a stressed exposure, so would still require additional modelling.

There is an available source of loss data, namely the 2014 EBA stress test data. In that stress test for MR, banks were provided with five scenarios (and a baseline scenario) and required to produce results for all of them (with the exception of AFS/FVO, which required only the macro scenario to be run). This data set has a number of strengths in light of the analysis above. First and foremost, the results of the stress are disaggregated into individual risk types so that analysis can be performed at individual risk level. All the data relate to the end of 2013. This means there is less of an issue with irrelevant data, as older data become less meaningful in a rapidly changing environment. All the data relate to simulated extreme events and not historical events, so the CCR issue discussed above is resolved. The cost of losses from counterparty default conditional on scenarios is available for analysis, instead of relying solely on the Lehman's event. There is also a benefit in using only extreme data to model losses. Potentially, relationships that exist in extreme events may not exist (or exist in a different form) in normal times and vice versa. This can be mitigated in credit risk modelling, where a significant time series of data is available (allowing for possibly sophisticated modelling), but would not be the case for MR data.

A drawback to this EBA data source is that it is from a stress testing exercise. It is not drawn from real world events. As such, the data source incorporates any weaknesses that stress tests have in modelling the reality of a stressed situation. These weaknesses would be incorporated into the TD forecasts. Worse still, if the weaknesses continue in a bank's stress testing projections, they may appear to be validated by the TD model, since the model is calibrated on data that are similar in nature. The weaknesses may only be revealed when a real world event occurs and the losses do not match the stress results.

Another drawback to the data is that they all come from one time period, namely the 2014 EBA stress tests, which are based on a starting point of bank data from the end of 2013. Moreover, the data are limited – only six instances for 90 banks. Credit risk models typically have far greater amounts of data. This drawback will be addressed over time as a larger set of stress test data can be built up.

Overall, then, a preferred approach to loss data is to use stress test results. For exposure data, the notional has been favoured.

3 Overall modelling approach

The previous section discussed the data set used for the analysis, with a broadly similar approach taken for modelling the data across all MR risk types discussed in this chapter. The exceptions will be looked at in the risk-by-risk analysis sections that follow this one.

The modelling is based on two sources of data about the banks: the notional of derivatives at the banks and stress testing losses from 2014. In addition, models also use data on the specific stress test and the size of the risk factor shocks from the market risk scenario in the stress test. This gives the scenario-linked move in various market prices. For example, the scenario might indicate that the Eurostoxx falls 30% (going forward, these will be referred to as risk factor shocks). The presented modelling brings together these three data sources. There are some challenges at a more granular level for these data.

The data include the notional split by asset class but not at a more granular level. There are figures for the derivatives notional with an equity underlying, and similarly for interest rate derivatives and other asset classes. However, there is not, for example, a split for equity derivatives denominated in Euro as opposed to US Dollar. The stress scenario contains a large number of shocks to a large number of instruments. Banks themselves have an even larger group of underlying instruments on which derivatives are based. In the models, this complex detailed and dis-aggregated portfolio of derivatives has been simplified. For each asset class, one shock is used for this asset class. For equity, for example, the shock to the Eurostoxx could be used if it was thought to be the best indicator of banks' exposure. Of course, it is possible to use a composite index made up of a number of different risk factor shocks but data constraints meant that only one could be used per asset class. The base equation for modelling is:

$$Stress\ losses^{j} \ = constant + \sum_{i=1}^{5} coefficient_{i} F\left(Asset\ Class_{i}, Notional^{j}\right)$$
$$* \ Asset\ class\ risk\ factor\ shock(i)$$

where i indexes the asset class type and j indexes banks.

The function of notional varies across risk types but is constant across asset classes. That is, the same function is used for all asset classes in one risk type.

This stylised equation provides the basis on which to perform linear regression to find the coefficients and assess the strength of the relationship. Linear regression has its drawbacks, not least in that it only looks at linear relationships and some of the relationships looked at may have non-linear elements. However, there is a significant danger of "overfitting" when using more sophisticated techniques. For some risks non-linear techniques are used, and it is an area that should be explored further in the future.

This equation essentially uses the asset class notional multiplied by the regression coefficient as the determinant of the stress losses given the market risk scenario. This combination is the risk metric that was discussed earlier. As already mentioned, it is an unlikely risk metric, which is discussed further in the following sections. However, the model, as it stands, is simple; the risk factor shock multiplied by the selected riskiness metric will provide the stress losses for the bank relating to the particular risk.

For a particular risk type, the notionals will vary across banks but the coefficients and shock sizes will not. Hence the different losses for each bank will be driven by the different asset class notionals. The regression coefficients and function of notional will vary across risk types. The risk factor shock[51] and the notionals will not. So for a specific bank, the losses will be different for each risk type because of the regression coefficients and the function of the notional.

4 Credit counterparty risk

Counterparty risk is the first risk that is looked at in this chapter. First, the way in which the methodology for counterparty risk worked in the 2016 and 2014 stress tests needs to be quickly reviewed, as it affects the way in which losses can be modelled.

To calculate losses from counterparty default in the 2016 EBA stress tests, banks were required to calculate their exposures to counterparties after the stress scenario. The banks would then rank their top ten exposures post-stress. From these exposures, they would choose the two counterparties most vulnerable to default. The selection would be based on which counterparties were most likely to default given that the scenario had occurred.

The major change for the methodology compared to 2014 was the change in the number of counterparties that default. In 2014, only the largest counterparty defaulted. In addition, the calculation of the LGD changed between the years. In 2014 the LGD was 100%, whereas in 2016 banks were required to calculate their own stressed LGD.

When using the 2014 data, one has to take account of the corresponding methodology. The LGD in the 2014 methodology was fixed at 100% so what was effectively looked at was the top counterparty's exposure after the stress scenario. Hence a standard equation should model top exposure rather than counterparty loss. To shift from that methodology, there is a need to move from the largest exposure to the stress loss however defined. As an example, for the 2016 EBA methodology, the

[51] It is possible to use different risk factor shocks for different risk types if those different risk factors are driven by different underlying instruments, but for simplicity's sake the risk factor shocks are kept the same across all the risk types here.

model uses a two-step process, first looking at the relationship between the top exposure and the exposure of the two must vulnerable counterparties and then looking at LGDs. For the analysis based on 2016 data, both steps were performed using expert judgment rather than modelling.

For stress testing, more generally, a direct modelling will give the top exposure. For a broader range of stress testing, there is a need to subsequently use expert judgement to move from the top exposure to the loss.

For the counterparty model, then, the standard equation and data discussed in previous sections are used, but the model forecasts the top exposure rather than the counterparty loss.

Regression on the 2014 data provides a very strong R-square. The linear regression shows an R-square of 77%.

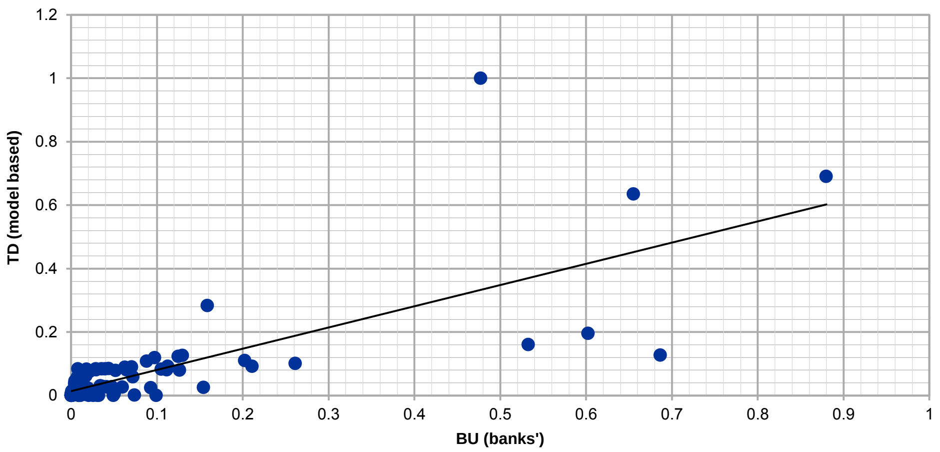
The results are strong for the 2014 data, but this does not contain any out-of-sample testing. For that, the 2016 data is needed.

The model continues to perform well on the 2016 data, although not as well as in 2014. Comparing the top exposures, the model produced an R-square of 57% (see Chart 6.1, note that the results have been normalised rather than use actual losses.) while total TD losses are 83% of the projections submitted by banks (the bottom-up (BU) results). The results of the total losses, that is after the two additional steps, which were guided by expert judgement, were much closer. The TD is 3% higher than the BU results, while the respective R-square is 88% (see Chart 6.2).

Chart 6.1

Counterparty credit exposures 2016

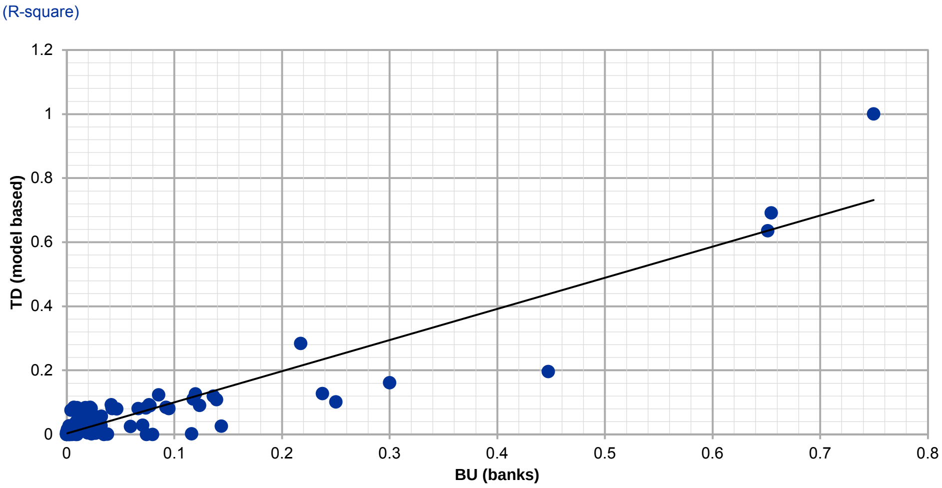
(R-square)



Source: authors computations.

Chart 6.2

Counterparty credit losses 2016



Source: authors computations.

The total losses comparison is perhaps not surprising, since it just means that the TD judgemental components (for the LGD and ratio of top exposure to the two most vulnerable counterparties) were more conservative than the BU results. But the R-square analysis is less straightforward to interpret. The results suggest that the TD model is better at explaining the two most vulnerable counterparties than the top one. When reviewing the submissions in detail, the reason became apparent; that is, four banks had unusual top exposures. These were top exposures that were a long way from the model and also had an unusual relationship to the other nine exposures for each bank. Excluding these four, the R-square comes back to a similar level to that of the 2014 data (about 86%). The overall level of the TD loss projection becomes 94% of the BU.

The model performs well on the 2016 data. The results show that there is a strong relationship between the chosen TD risk metric, the notional and losses. As mentioned earlier, there were, however, reasons to doubt the existence of the relationship. The variability of the derivative pay-out and sensitivity to stress would appear to mean that the notional is a poor metric. Further, the dynamism of the banks' derivative portfolios would also lead one to question the applicability of the notional.

One of the key reasons for the strength of the relationship could be that, although there is a wide range of different types of derivatives in any bank's portfolio (the composition of which varies between banks and over time), the key drivers of the loss are similar among banks and fairly constant over time. The post-financial crisis environment could have significantly helped in this. Banks' portfolios have become simpler. It does reinforce anecdotal evidence that banks' portfolios (for counterparty risk at least) are mainly driven by vanilla instruments.

The results highlight two other points about the model. There were four significant deviations from the model which were correct in their BU calculations. There does seem to be a level of idiosyncrasy that is hard for the model to fully predict, and it is clear that MRTD models, as they exist, could not replace BU analysis in individual banks' capital calculations. But these idiosyncrasies do provide a use for the model too. These deviations can reveal features of the bank's business model or risk-taking attitude that can be used in the general supervision of banks.

The model can make suggestions about the overall market in counterparty risk. Banks' risk-taking generally (with the four idiosyncratic cases excluded) appears to be in line with the previous stress test in 2014 – the overall results of TD and BU are similar in both cases. This was not the case across all risk types, as documented in the following sections.

The TD model would also suggest that counterparty risk is becoming more idiosyncratic, with that idiosyncrasy being generally on the upside (that is, through higher risk concentration). However, the evidence for this is not huge, with four banks out of the 91 in the stress test responsible for most of it. It may, however, support causal observations that an increase in the syndication process (and a greater reliance thereon) may lead to more dynamic counterparty exposure.

The model will require further validation from future stress tests to reach the level of confidence that other TD models have, but there is clear evidence for the model as it appears to fit the available data to a very large extent. And that in itself shows that the notional can be a predictor of losses in a stress test.

5 Market liquidity

Market liquidity is a stress on the bid/offer reserve that banks hold. Again, a review of the EBA methodology is required to understand the loss data the model uses. The methodology requires a bank's bid/offer reserve to be multiplied by a percentage that is given in each scenario. To model this stress, the current bid/offer reserve of banks is multiplied by the percentage given in the scenario.

A model similar to the general MRTD model equation already presented can be used, simply replacing the notional by the fair value of assets. These are split by accounting classification of liquidity: level 1, 2, and 3. Level 3 instruments are the most illiquid; level 1 instruments the most liquid. The asset class risk factor shock is excluded (it is not directly relevant to the change in bid/offer and the fair values in the data are not split by asset class), keeping the regression coefficient to work with the fair values. The resulting equation reads:

$$bid\ offer\ reserve_{Bank\ i} = b_0 +$$
$$b_1 * \ Level\ 1\ \ FV_{Bank\ i} + +b_2 * \ Level\ 2\ FV_{Bank\ i} + \ + b_3 * Level\ 3\ FV_{Bank\ i}$$

where i indexes the banks and b is the regression coefficients. The concept behind the model is again quite simple. There is a need to find a relationship between the bid/offer reserve and the quantity of assets in the three accounting classifications. It could be generally assumed that the bid/offer reserve for a particular instrument would increase as the instrument becomes less liquid.

Bid/offer reserves themselves are not stressed in the EBA methodology, rather the stress loss is the product of a multiplier, which is tied to each scenario, and the bid/offer reserve before the stress. The methodology was the same in EBA 2014. The practical implication of this is that there is only one scenario against which to regress in 2014. All scenarios would have the same underlying bid/offer reserve. So each scenario result for the stress in this risk type would vary only by the relative difference in the multipliers.

For derivatives, the bid bid/offer reserve calculation can be complex since it is often risk-based rather than based on fair or notional value. There is also often a large amount of offsetting in the risk methodology.

The estimation of the model reveals a strong relationship in the 2014 data, with the R-square over 90%.

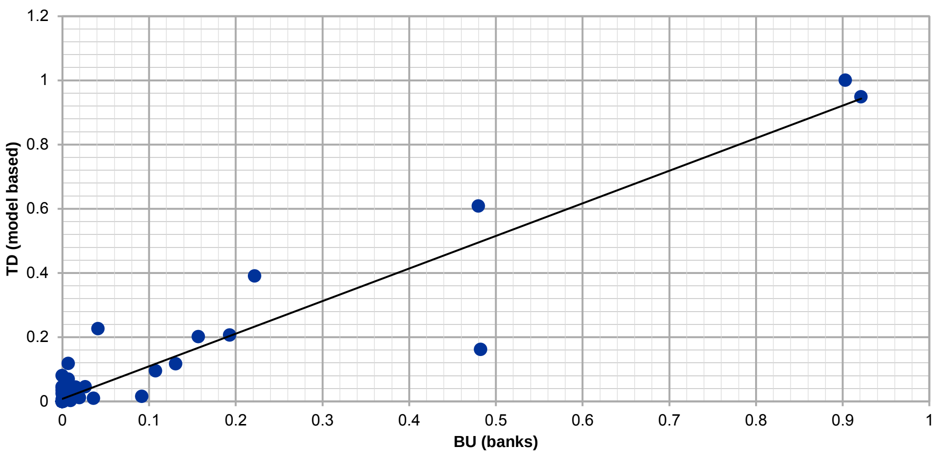
Linear regression does, of course, have its weaknesses. What is clear in this result is that the larger banks are well fitted whereas the smaller ones are less well fitted.

The model itself shows that level 3 assets are a very significant driver of the liquidity reserve. This balance may not be appropriate for smaller banks and this may call for having a more sophisticated approach for the model to be able to capture all banks well.

When the model is run against the 2016 EBA results it reinforces the points from the 2014 data. Overall, the model performs very well with an 89% R-square (see Chart 6.3, again the losses have been normalised). However, the fitting for the smaller banks is again weaker than for the big banks. Excluding the top five banks by size of market liquidity stress reduces the overall R-square to 66%. Overall, the TD results are 120% of the BU, while the exclusion of the top five means the TD is about double the BU result.

Chart 6.3
Market liquidity losses 2016

(R-square)



Sources: authors computations

As mentioned earlier, the model effectively forecasts the size of the bid/offer reserve from the fair value of the assets and liabilities, broken down into their three accounting classifications. This would imply that banks keep a similar reserve even though they may have different products in their portfolios. The main driver is just the size of the fair value. Although banks have different portfolio mixes and bid/offer reserve methodologies, the key driver in the size of their reserve is the fair value of assets broken down into liquidity type. There are similarities to the counterparty risk model in this respect. While banks have different portfolios with a different mix of instruments, the key drivers of the reserve are actually quite similar.

6 Counterparty valuation adjustment (CVA)

As with the other sections, there is a need to first review the EBA stress test methodology to better understand what the loss data actually represents. Within the EBA 2016 methodology, the CVA methodology was linked to that for counterparty. Banks were required to fully revalue their CVA after the stress scenario taking into account changes in exposure due to the stress shocks and changes in credit spreads from the scenario.

The key difference from the 2014 methodology is the second part. In 2014, banks were required to calculate their exposures to counterparties after the stress scenario, but rather than using their own CVA models and stressed credit spreads, they were required to use the standard haircuts given in the scenario.

The TD model again uses the standard equation in section 2 for the regression for CVA. However, the part that is modelled is not the CVA loss but the change in exposure. So, as with the counterparty model, there is a two-part model. The first part models the change in exposure using the 2014 data and the standard regression-based technique. The second part consists of an analytical approximation for turning the exposure into a CVA using the stressed credit spreads. Both work as a percentage increase on the starting point for CVA, which is provided by banks in the EBA templates.

The templates also subdivide the CVA into those for sub-investment grade (SIG) counterparties and those for investment-grade (IG) counterparties in both the 2014 and 2016 results. This allows us to review the models' outputs in these sub-categories.

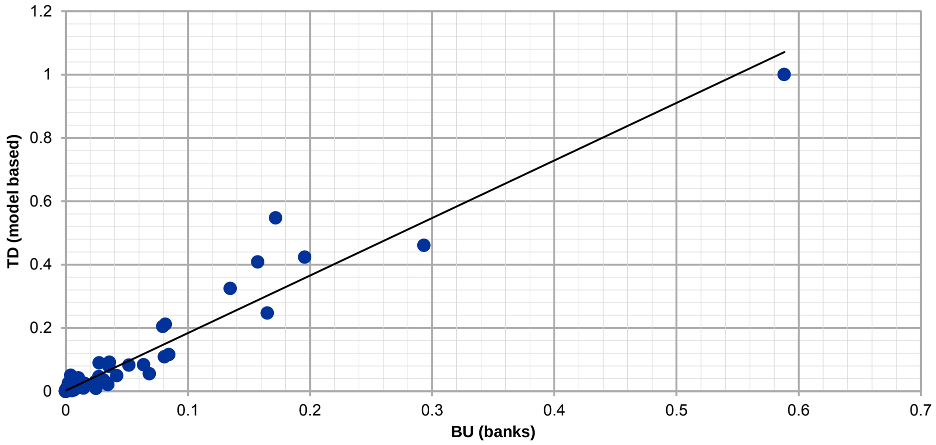
The model produces a worse fit than the counterparty model on the 2014 EBA stress data on which it is calibrated. The R-square of the model is about 45%. The results are a little better for IG than SIG, but not enough to consider following a separate modelling course for each. There are some potential reasons for the lower R-square. One of the reasons the counterparty model works well is that it models a large portfolio where it is difficult for individual positions to dominate; CVA portfolios, by contrast, tend to be mainly driven by a smaller number of positions (the bulk of CVA typically comes from uncollateralised trades, the majority of overall trades are collateralised). This means that CVA might be more susceptible to being dominated by idiosyncratic trades, which the TD model cannot capture. Generally, SIG portfolios are likely to be more susceptible as they are smaller, and there are indeed worse results for these portfolios. This "idiosyncrasy" need not be very idiosyncratic. For example, the same FX shock applies to all notionals. If one bank then had a greater level of Asian trades in the uncollateralised portfolio than the norm this would cause problems for the envisaged model.

The overall TD losses that the model produces are slightly below the BU 2014 results as well.

Chart 6.4

CVA losses 2016

(R-square)



Source: authors computations.

The results of the model on the 2016 data are good, possibly surprisingly so. The model produces a very high R-square, above 90% (see Chart 6.4). This is higher than the r-squared on the data on which the model is calibrated. However, the model produces overall losses that are considerably higher than (over double) the BU results.

There are potential explanations for this largely unexpected good fit. It is also possible that the results are just much better by coincidence and thus overstate the explanatory power of the model. Further testing will be needed in order to evaluate both options.

The potential explanations for the performance of the model are somewhat in-depth. There has been considerable change in the regulations facing markets' banking activities. In addition, banks have changed their risk-taking behaviour following the financial crisis. This has in, general, led to banks taking on lower CVA risk. Thus, it is not difficult to believe that there has been an industry-wide reduction in exposure to CVA. This has been achieved by collateralising more deals and by not continuing with some maturing deals. The new deals that have been entered into are generally significantly more vanilla than they were before the crisis. This "vanilla-ness", or simplicity, applies to both the type of derivative and the underlying to the derivative. In 2016, there would be fewer pre-crisis deals left than in 2014. This, in addition to the reduction in the overall CVA exposures, may have made banks' exposure less idiosyncratic. This would make the selected TD model work better too.

The argument – one that certainly needs further evidence to prove it – is that the regression on the 2014 data identifies a systematic effect of vanilla CVA deals, but in those data there are also a lot of idiosyncratic effects, which means the overall explanatory power of the model is not great. In 2016, the same systemic effects are at work with vanilla CVA deals, but this effect is much more dominant.

The CVA analysis does highlight an issue for the model. It is difficult for the model to cope with changes in the overall market. With only one time slice in the sample regression, the model is never going to be able to allow for the reduction of CVA over time. Even the addition of another time period, 2016, would not provide much more help as it might project a similar rate of decline going forward, when in fact it is likely that the rate of decrease of CVA will slow down going forward. But, as with counterparty, this weakness in the model also provides an opportunity to consider how much stress exposure to CVA is decreasing over time.

There is the potential for another weakness in the model to significantly overstate the change in CVA exposure. The model is based on linear regression (although the function of the notional is not linear). For other areas (specifically counterparty) non-linear models were tried but not for CVA. It is likely that the relationships are non-linear and this might change the overall impact of the TD model.

The CVA model results give rise to some slightly counter-intuitive comparisons between counterparty and CVA. This suggests that CVA is declining in risk exposure but counterparty is not, which is understandable. But it would be counter-intuitive to suggest that counterparty is becoming more idiosyncratic while CVA is becoming less so.

7 Held for trading (HFT) model

The model for HFT is substantially different from the other models. It does not regress against the derivative notional. One of the reasons why such an approach will likely not work is because the portfolio for HFT is very dynamic in terms of stress test loss outcome. For some parts of the portfolio it is possible to switch from being loss-making in a stress test to profit-making within a day. It is the only part of the MR stress test that can return profits (in theory, AFS can too, but in practice, it does not) in a stress test.

Again the modelling strategy is to leverage the data provided in the EBA stress test. The data include risk sensitivities per risk factor and VaR for each asset class. The MRTD model calculates a stress loss using the risk sensitivities and an own estimate of asset class VaR using these. The model compares its own VaR estimate to the bank's VaR. The bank's VaR should capture more risks than the own estimate does, so as a comparison, it shows the size of risks not captured by the risk sensitivities. The model then scales the calculated stress result by the ratio of the bank's VaR to the own estimate VaR to get a final loss estimate. This final adjustment aims to capture the risks not present in the reported risk sensitivities.

Unlike the other models discussed in this chapter, this HFT model cannot be used in a stand-alone top-down stress test, as it requires data specific to the EBA stress test. As such, a separate model is needed for stand-alone TD work, such as is needed for macroprudential purposes.

As mentioned at the beginning of this section, the difficulty for HFT is the dynamism of the portfolios. The dynamism of individual positions is, unsurprisingly, linked to the liquidity of the instrument. Instruments that are liquid can be sold and bought quickly and therefore their positions can change quickly. In addition, it is also usually easier to short liquid instruments, meaning that it is possible to show profit in a stress test scenario.

One way to reduce the impact of liquid positions (which are the hardest to model) is to make the methodology liquidity-sensitive. In this type of methodology, the size of the risk factor shocks varies depending on the liquidity of the instrument. The shocks are accordingly bigger for the illiquid instruments and smaller for the liquid ones. As such, it makes the contribution from liquid instruments smaller and the contribution from illiquid instruments larger. As the illiquid instruments are more stable, this brings greater stability to the stress results and makes it easier to model. It is possible that such methodology would enable HFT models to function more like CCR ones where the significant drivers of losses are more stable over time.

8 Conclusion

This chapter has looked at four new MRTD models. These models use a simple construct to produce strong explanatory powers. The models broadly use the notional as a risk metric to be used in combination with the market risk scenario to produce TD model losses.

The detail, of course, is more complex, but it does not obscure the fundamental and most striking part of this work: that the notional can be a good predictor of losses for MR stress testing. The estimated TD models produced strong R-square across CVA, counterparty and market liquidity.

One of the inferences that can be drawn from the results is that, while banks have different portfolios with different mixes of products and sizes, the key drivers of stress losses across the banks are similar. It is likely that these products are the more vanilla ones. This would suggest that, for the risks that have been reviewed, the key focus is the size of the simple products that are in the portfolio rather than the details of the complex instruments in the portfolio. These results may be driven by the rationalisation of the markets' business model after the financial crisis and the evolving regulatory landscape.

These models are brand new additions to the TD suite of models that can be employed for macroprudential stress testing. There are a number of ways in which these models could be deployed. As noted at the start of this chapter, market risk is not the biggest exposure for European banks at the macro level. As such, it is less likely to be a driver of significant stress by itself (except where very large banks would be severely hit by MR alone). However, in the past it has been seen that market risk can exacerbate situations that have other drivers. One of the important issues with market risk, at a macroprudential level, is understanding its links to other risks and, in particular, understanding in which situations MR increases losses driven by other risk categories.

One of the issues with MR which makes this difficult is its opacity and dynamism. Some of these features that affect MRTD were reviewed in this chapter. In addition, there is the fact that any stress test methodology for MR is not easy to design. As such, MR stress testing methodologies therefore show greater change over time and more variability between regions. The detailed risk sections give a number of examples where the EBA methodology changed between 2014 and 2016. Another example would be the contrast between the HFT methodology of the EBA and the Bank of England. The latter uses a liquidity-adjusted approach with different shocks depending upon the liquidity of the instrument, while the EBA uses the same shocks for all instruments.

One of the potential uses for the MRTD models is to explore connections between risks by varying some of the methodologies. One example would be to look at the effects of a number of significant credit downgrades or defaults at large corporations and financial companies. Most counterparties to derivatives fit into these two categories and so this can be a significant addition to losses and the instability that would arise from the losses due to credit risk. By altering the counterparty methodology to allow for more defaults (and synchronising it with the credit methodology) and potentially by varying the number across banks (depending on the riskiness of the portfolio), it could provide greater understanding of the impact of such a scenario and the link between credit and MR for large institutional exposure.

Looking at broader macroprudential stress testing, MR models can provide a greater understanding of the impact of scenarios that cause difficulties for other financial companies, such as insurance companies. Through system-wide stress testing and the more realistic overview that MRTD models provide, one can gain a greater insight into the impact of such scenarios on the wider financial system.

Overall, this work represents significant progress – with all the drawbacks and caveats previously mentioned – towards a series of MRTD models that can have a wide variety of uses. The modelling base and conceptual framework are substantially different from those used for other risks and, as a result, some of the potential uses or the way the model outcomes are interpreted may also differ.

Chapter 7 Satellite model for top-down projections of banks' fee and commission income

By H. Mirza, D. Moccero and C. Pancaro[52]

While substantial effort has been directed at modelling loan losses and net interest income components, only a few empirical studies have focused on fee and commission income (F&C), despite its significance as the second most important source of revenue for the majority of euro area banks after net interest income. Indeed, F&C constitutes, on average, between 20% and 30% of euro area banks' total income and about two-thirds of banks' total non-interest income.

The sensitivity of banks' F&C to adverse macroeconomic and financial developments has not been a major concern in previous stress testing exercises (for example EBA EU-wide stress tests). Indeed, this income component has often been assumed to be stable. However, this assumption is over-simplistic and disregards the fact that F&C has exhibited some cyclical features. Therefore, treating this item as independent of macro-financial developments when conducting supervisory and macroprudential stress tests could lead to an underestimation of banks' income sensitivities to the macroeconomic environment.

Against this background, this chapter proposes a panel econometric framework for estimating the relationship between some key macroeconomic and financial factors and F&C using yearly bank-level data between 1995 and 2015 for a large sample of euro area entities. It then suggests using the estimated parameters to project F&C over the stress test horizon and presents illustrative results of F&C projections conditional on scenarios similar to those of the 2016 EU-wide stress test.

1 Description of the data

This analysis uses an unbalanced panel of annual data from 1995 to 2015 for a sample of euro area banks established in the 19 euro area countries. The variable of interest is F&C over total assets. This item includes commissions and fees earned from service charges, brokerage fees, origination and servicing fee income from the servicing of mortgage loans, credit card receivables, automobile loans and other consumer and commercial loans, trust fees, management fees and investment banking fees, and fees and commissions earned from real estate management services (e.g. fees for property acquisition and development, advisory fees, asset management fees, facilities management fees and related real estate services). The

[52] This work is partly based on C. Kok, H. Mirza and C. Pancaro (2017).

coverage of banks tends to increase over time, i.e. the most recent years typically have the best coverage. The banking data were extracted from Bloomberg.

The dataset used in this analysis includes 103 banks.[53] The most represented countries are Germany (20 banks), Italy (14 banks), Spain (12 banks) and France (10 banks). Estonia has only one banking institution in the sample.[54]

The dataset also includes a series of potential macroeconomic and financial variables for the euro area countries. This set of explanatory variables was selected to reflect variables considered in the literature and also takes into account the need to include only variables that are projected in the macroeconomic scenario. These explanatory variables are both the contemporaneous value and the first lag of each of the following: the rate of growth of the stock market, the change in short and long-term interest rates, real GDP growth, residential real estate prices and the HICP annual inflation rate. The macroeconomic and financial variables were extracted from the ECB Statistical Data Warehouse.

2 Some stylised facts

In the last few years, strong competition on traditional intermediation activities and a fall in interest income due to a low interest rate environment strengthened banks' incentives to develop non-interest income business activities.

Taking a longer-term perspective, the median ratio of F&C to total assets in the sample of euro area banks under consideration has stood between 0.6% and 1.2% over the last fifteen years (see Chart 7.1). At the same time, the median ratio of F&C to net revenue[55] (see Chart 7.2) for the same sample of banks has hovered between 20% and 30%.[56] More specifically, three phases of the median evolution in these variables can be distinguished. Indeed, F&C (both relative to total assets and to net revenue) is increased from 1995 to around 2000, decreased until 2007 and was relatively stable thereafter. However, the median evolution of these F&C ratios conceals substantial heterogeneity across euro area countries.

53 All euro area banks included in the EBA stress test sample, except for NRW in Germany for which data were not available, are part of this panel.

54 The number of banks included in the forecasting sample is slightly lower than the number of banks included in the estimation sample due to lack of data for some banks in the last few years of the sample. Lack of data towards the end of the sample affects mainly France and Lithuania, but also Estonia and Spain.

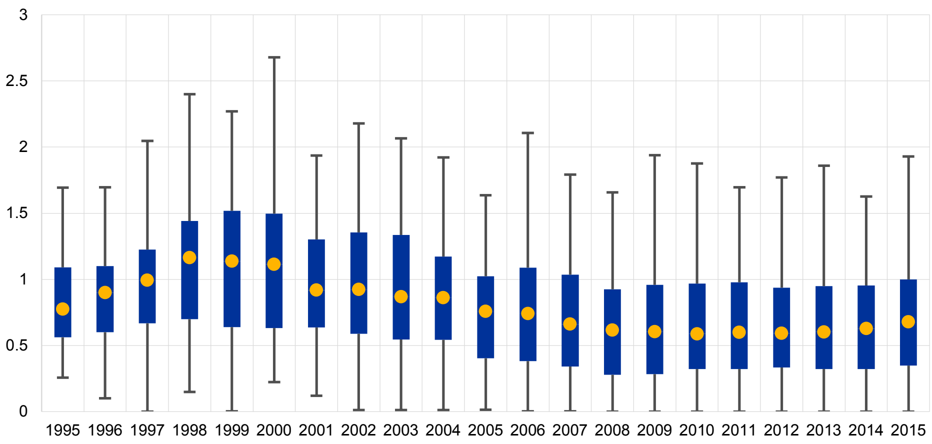
55 Net revenue is the sum of interest income, trading account profits (losses), investment income (losses), commissions and fees earned, and other operating income, minus interest expense.

56 Although this ratio is only half of that of net interest income over net revenue, it still indicates that fees and commissions are an important source of revenue for euro area banks.

Chart 7.1

Fee and commission income over total assets

(percentage, 1995-2015)

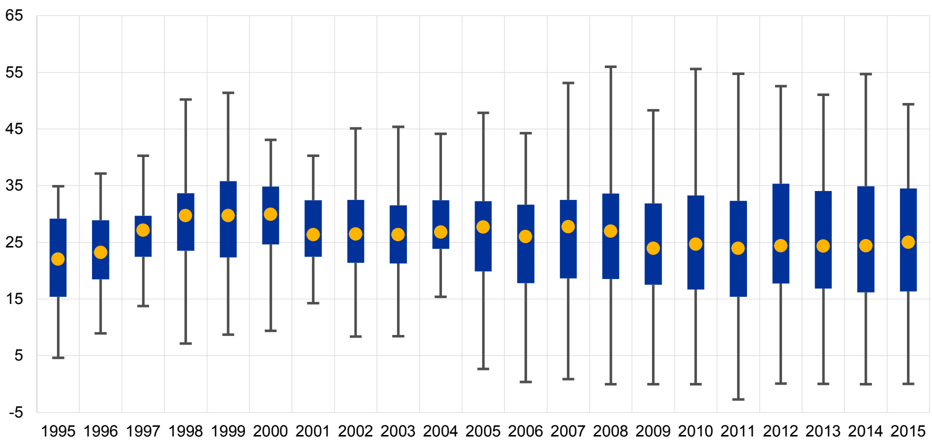


Sources: Bloomberg and authors calculations

Chart 7.2

Fee and commission income over net revenue

(percentage, 1995-2015)



Sources: Bloomberg and authors calculations

3 Variable selection: the Least Angle Regression procedure

There is a large set of candidate factors that may be associated with developments in the ratio of F&C to total assets. In order to examine which variables are the most relevant in influencing the dependent variable, a variable selection procedure is applied. Indeed, in the presence of many candidate variables, the objective is to choose as regressors those variables that have the most explanatory power for the variable of interest, while keeping the model relatively sparse to avoid over-fitting.

For the purpose of variable selection, the Least Angle Regression (LARS) algorithm (developed by Efron and Tibshirani, 2004) is used.[57]

In this analysis, the initial set of variables to which the LARS algorithm is applied comprises the lagged F&C over assets, stock market returns, the inflation rate, real GDP growth, the first difference of the short- and the long-term rate, the house price index, and the lags of each of these macroeconomic and financial variables. This set of variables is determined relying on the economic rationale and on the related empirical literature (see, for example, Covas, Rump and Zakrajšek, 2014) and includes only macroeconomic factors, as these are the variables which are typically included in stress test scenarios.

Table 7.1

LARS: Selection of variables included in the model

Step	Cp	R-square	Variable added
1	10,835.05	0.00	
2	114.57	0.8984	F&C income over assets (t-1)
3	60.22	0.9031	Short-term rate first difference(t-1)
4	62.08	0.9031	Stock market returns(t-1)
5	20.41	0.9068	Stock market returns
6	15.22	0.9074	Long-term rate first difference(t-1)
7	14.66	0.9076	House price index growth
8	6.39*	0.9085	Real GDP growth
9	8.05	0.9085	Inflation rate(t-1)
10	9.91	0.9085	Short-term rate first difference
11	11.41	0.9086	Long-term rate first difference
12	11.43	0.9087	House price index growth(t-1)
13	13.03	0.9088	Real GDP growth(t-1)
14	14.00	0.9088	Inflation rate

Sources: authors calculations
Note: The table shows results based on the LARS variable selection algorithm. At each step of the procedure the Cp statistic, the R-squared of the model and the newly included variable is provided. The model with the minimum Cp value is marked with *.

Table 7.1 shows the results of the variable selection procedure. More specifically, Table 7.1 provides the order of inclusion of each variable, a statistic at each step for the resulting model, as well as the R-square implied by the individual models. Efron and Tibshirani (2004) suggest selecting the set of variables as implied by the minimum value of the Cp statistic. The model implied by the minimum Cp statistic includes eight out of the fourteen candidate variables (including the constant). The variable set selected using the LARS approach comprises, in decreasing order: the lag of fee and commission income to assets ratio, the lagged first difference of the short-term rate, stock market returns, the lagged stock market returns, the lagged first difference of the long-term interest rates, residential property price growth and real GDP growth.

[57] This approach is similar in spirit to the one employed by Kapinos and Mitnik (2016). The authors use the Least Absolute Shrinkage Operator, which is a constrained version of LARS, also for variable selection in a stress testing context.

4 Econometric framework

The estimated model aims at detecting cyclical features in F&C, using a panel data econometric framework. The model is specified as follows:

$$y_{it} = \mu_i + \alpha y_{it-1} + \beta X_{it} + \varepsilon_{it} \quad (1)$$

Where $\mathrm{y_{it}}$ is the F&C over total assets for bank i and period t, $\mathrm{y_{it-1}}$ is the lagged dependent variable, $\mathrm{X_{it}}$ is the vector of explanatory variables identified by the application of the LARS methodology, $\mathrm{\mu_i}$ is a bank fixed effect and ε_{it} is an idiosyncratic shock.

Because the inclusion of the lagged dependent variable might yield biased and inconsistent estimates owing to the correlation between the lagged dependent variable and the error terms, Equation (1) is estimated using a system generalised methods of moment (GMM) estimator[58] (Blundell and Bond, 1998)[59].

Table 7.2

Fee and commission income: regression results

Variable	Coefficient
F&C Income/Total Assets(t-1)	0.8066***
Short-term rate second difference	-0.0180***
Stock market returns(t-1)	0.0003
Stock market returns	0.0005**
Long-term rate second difference	-0.0009
Real GDP growth	0.0053*
Residential property price growth	-0.0008
Constant	0.1277**
Number of obs.	1,119
Diagnostic statistics	
AR(2) Arellano-Bond test (p-value)	0.27
Hansen J test (p-value)	0.11

Sources: authors calculations
Note: ***, **, and * denote significance at the 1%, 5% and 10% level, respectively.

The estimates, reported in Table 7.2, show that the lagged dependent variable, the lagged first difference of the short-term interest rate, stock market returns and real GDP growth are the significant explanatory factors. The signs of the estimated coefficients are all as expected and in line with the previous literature. More specifically, the results show that F&C over assets is persistent as the lagged dependent variable is an important predictor. The first difference in the short-term interest rate is negatively associated with the dependent variable, suggesting that a fall in interest rates that leads to a compression of interest margin may force banks to search for other sources of income.[60] The stock market returns are positively related to fee and commission income, owing perhaps to the charging of fees associated with stock market transactions (e.g. securities brokerage).[61] Finally, real GDP growth is also positively associated with the dependent variable. This might indicate that a better-

[58] In particular, a one-step estimation approach with robust standard errors is applied.

[59] The inclusion of a lagged dependent variable in a panel framework might yield biased and inconsistent estimates owing to the correlation between the lagged dependent variables and the error terms. This is referred to as dynamic panel bias; see, for example, Nickell (1981) and Kiviet (1995).

[60] Covas, Rump and Zakrajšek (2014) also find that a decrease in the short-term rates is associated with an increase in non-trading non-interest income.

[61] Coffinet, Lin and Martin (2009) also use a dynamic panel approach and find that stock market growth is a main driver of fee and commission income in a large dataset of French banks between 1993 and 2007. Exploiting Swiss banking data between 1994 and 2007, Lehmann and Manz (2006) also find that lagged commissions and positive stock market returns are positively associated with higher commission income.

performing real economy could imply an expansion of those financial services (e.g. M&A) that generate fee and commission income.[62]

To illustrate the behaviour implied by such equations, the estimated parameters in Table 7.2 are then used to project the F&C ratio, conditional on macro-financial scenarios in line with the baseline and the adverse scenario of the 2016 EU-wide stress test.[63] Bank-specific F&C over assets projections based on the suggested model are computed year by year and then aggregated at country level as a weighted average of the individual banks, using the respective shares in the countries' total assets.

Overall, F&C projections appear sensitive to the different macroeconomic developments. As expected, the projections are consistently more conservative under the adverse scenario than under the baseline scenario. More specifically, while the projected F&C ratios decline for almost all banks with respect to the 2015 starting point under the adverse scenario, baseline projections increase in some cases.

Chart 7.3 shows the distributions of the F&C projections aggregated at country level for 18 euro area countries under the adverse scenario.[64] For each country, the projections over the three-year horizon are reported in terms of percentage changes with respect to the cut-off date. The adverse scenario has its strongest impact in the second year of the stress test horizon.[65] While in the first year F&C drops by less than 5% for the majority of the countries, this changes in the second year, when seven countries would see their banks' F&C decline by between 5% and 15%, and four countries by even more. This is in line with macroeconomic scenarios which exhibit the trough in the second year. The impact eases somewhat in the third year when there are only two countries for which the decline in the F&C projections with respect to the starting point exceeds 15%.

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[62] The Arellano-Bond test does not reject the null hypothesis of the absence of autocorrelation of second order in the estimated residual, and the Hansen test does not reject the hypothesis that the instruments are valid (i.e. that the instruments are uncorrelated with the error term).

[63] It is also worth noting, however, that the EBA Methodology on most non-interest income items and, in particular, F&C was very prescriptive and the corresponding outcome would thus not be directly comparable with that produced by the top-down F&C model presented in this chapter.

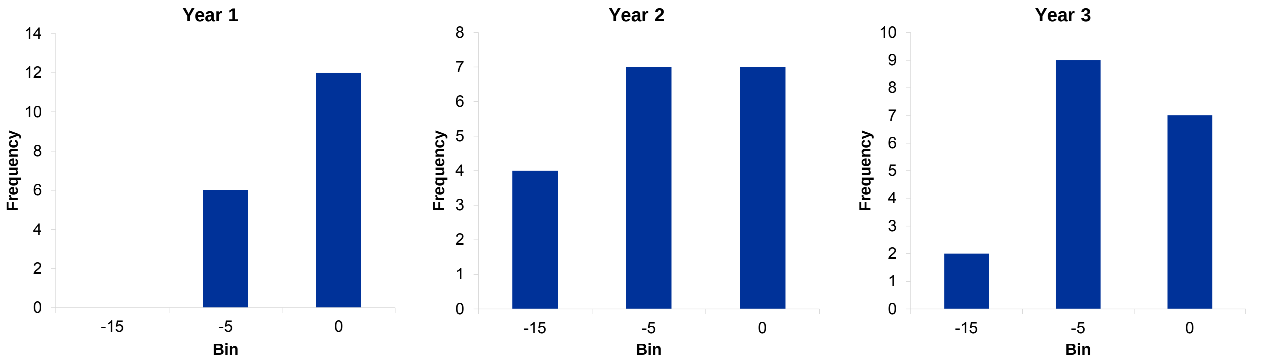
[64] For Lithuania, all the banks exhibit lack of data over the last two years of the sample.

[65] The variations in F&C over the stress test horizon described hereafter are expressed as changes with respect to the cut-off levels.

Chart 7.3

Distribution of F&C projections at country level under the adverse scenario, by stress test year

(percentage, change with respect to the cut-off level)



Note: authors calculations

5 Conclusion

This chapter has presented an empirical macro-financial model for the estimation of F&C (as a ratio of total assets) for a broad sample of euro area banks. A variable-selection technique (LARS) was first used to determine the set of relevant regressors for the variable of interest. Then, using panel econometric techniques, estimated equations show that F&C over assets varies with the economic and financial cycle. Finally, using the estimated parameters, illustrative projections of the ratio of F&C to assets can be generated over a three-year horizon conditional on both a baseline and an adverse macroeconomic scenario.

This analysis illustrates how F&C are sensitive to different macroeconomic developments. Indeed, the resulting F&C projections aggregated at country level are more conservative under the adverse scenario than under the baseline scenario. Indeed, while under the baseline scenario some countries would record an increase in F&C, under the adverse scenario, all countries would experience significant drops in this source of income. Importantly, however, the decline in F&C would present a substantial variation across countries.

These findings suggest that stress tests assuming scenario-independent F&C projections are likely to be flawed. Ignoring this would presumably lead to a misrepresentation of banking-sector soundness and resilience to shocks.

Going forward, it would be interesting to develop further research in this field to investigate how the sensitivity of F&C to macroeconomic developments depends on banks' specific business models. A first attempt in this regard was recently made by Kok, Mirza, Móré and Pancaro (2016). Moreover, data availability permitting, it would be appealing to conduct similar analyses for more granular and homogeneous definitions of F&C.

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Chapter 8 Operational risk module of the top-down stress test framework

By Anthony Bousquet and Tomasz Dubiel-Teleszynski

Over the past few years, operational loss amounts have materially increased. Mostly driven by misconduct losses[66], this increase has magnified the sensitivity of banks' results to operational risk in general, calling for a refined top-down approach encompassing all components of operational risk as a building block complementing the ECB staff top-down toolkit. As such, the creation of the top-down module coincides with the EBA's interest in this specific risk, as shown in the 2016 EBA stress test methodology. The purpose of the operational risk model is to provide a consistent approach using the full granularity of reported data, namely the 2016 stress test data, while fully complying with regulatory guidelines and industry best practices.[67]

In the context of stress testing, the impact of operational risk can be broken down into two distinct categories: profit and loss (P&L) impact and the impact on capital requirements. A significant challenge for a top-down approach to operational risk is to capture individual banks' peculiarities with respect to capital requirements calculations. Regarding the projection of losses, one subcategory is not yet incorporated in the operational risk top-down module, namely material conduct losses. The reason is that these losses have been substantial in recent years, yet without sufficiently granular and consistent data to assess properly possible linkages with, for example, the nature of individual business models. This is one of the features currently under investigation, for possible inclusion later on in the operational risk module. Table 8.1 below contains a recap of the subcategories covered by the top-down module, which are further developed in this chapter.

The top-down approach is built upon severity distributions (amount of loss per event) and frequency distributions (number of events per year) at bank level. Monte Carlo simulations combine frequency and severity distributions to produce the aggregate loss distribution, i.e. the distribution of annual loss outcomes. Individual projections estimated via this probabilistic top-down approach can then be aggregated into system-wide projections.

The chapter has two main sections, both of which present the core of the model; Section 1 describes the modelling of the P&L impact, while Section 2 discusses the projection of capital requirements.

66 According to ESRB (2015), misconduct losses totalled around €200 billion for all banks and €50 billion for EU banks over the 2009-14 period, with a gradual annual increase throughout the period.

67 The authors are grateful to the Oesterreichische Nationalbank for providing a database enabling this test to be performed. The Austrian loss data collection comprises 54,000 individual events collected from 2007 to 2013, slotted into the regulatory business lines and event types, for 23 Austrian banking groups.

Table 8.1

Mapping of the subcategories of operational risk using the top-down modelling approach

<table>
<tr><th></th><th></th><th>P&L</th><th>Capital requirements</th></tr>
<tr><td rowspan="2">Conduct risk</td><td>Non-material events</td><td>Simulation approach
(specific to P&L projections)</td><td rowspan="3">Simulation approach
(specific to capital requirements projections)</td></tr>
<tr><td>Material events</td><td></td></tr>
<tr><td colspan="2">Other operational risk</td><td>Simulation approach
(specific to P&L projections)</td></tr>
</table>

1 P&L impact

Operational loss projections are given by summing up the loss projections of the three underlying subcategories: other operational risk losses, non-material[68] conduct risk losses and material conduct risk losses.[69] As shown in Table 8.1, two of them – other operational risk and non-material conduct risk – are projected in a top-down manner.

The top-down approach for the projection of losses is to fit a lognormal distribution[70] to estimate severity (amount of loss per event), using granular data to fine-tune the fit. The variance is derived from the Austrian loss data collection[71]. The Negative Binomial distribution was deemed the most relevant to model frequency distribution (i.e. number of events per year). The availability of bank-level data bucketed by loss amounts, for both frequency and severity, allows the estimation of distributions for each bank at bucket level. Such an approach assumes independence across buckets[72], i.e. for each bank the volume of loss in bucket b_1 is assumed not to affect the volume of loss in buckets b_2 to b_x (and vice versa). In the absence of granular bank-level information on dependence, the model also assumes independence across individual losses. The modelled frequency and severity distributions are then

68 Materiality for conduct risk events is defined as 10 basis points of CET1 capital.

69 *Conduct risk* is defined in accordance with definition in EBA (2014): "current or prospective risk of losses to an institution arising from inappropriate supply of financial services including cases of wilful or negligent misconduct". In EBA (2016), conduct-related losses are approximated by the regulatory event types 1 ("Internal Fraud") and 4 ("Client, Products, Business and Practices"). *Other operational risk* is defined as the risk of losses that are not conduct losses.

70 The lognormal distribution is a widely used distribution in the field of operational risk that is also in line with regulatory requirements.

71 To specify the variance, loss data at the highest level of granularity was required, i.e. a database displaying individual loss events. The Austrian loss data collection featured the required level of detail, and was used to calibrate the variance parameter.

72 The independence assumption for levels of losses between individual buckets and, consequently, the summation of losses simulated at bucket level to arrive at aggregate loss distribution, as also outlined in Table 8.2, are based on the characteristics of the chosen frequency and severity distributions coupled with the results in the mixed Poisson distribution theory (such as infinite divisibility of distributions), see for instance Karlis and Xekalaki (2005).

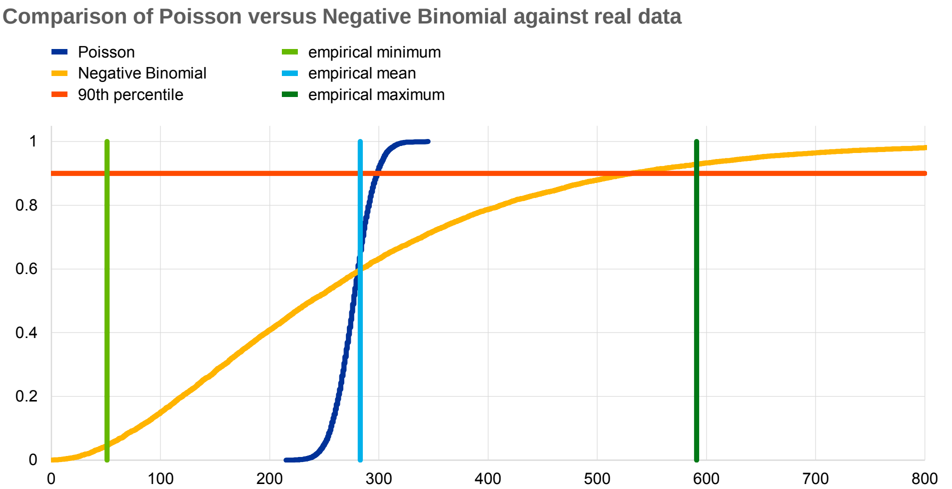
combined through Monte Carlo simulations to obtain the aggregate loss distribution. The chosen percentile of this distribution yields the estimated annual loss. The 2016 EBA stress test exercise posited that the baseline scenario would correspond to the median and the adverse scenario to the 90th percentile at bank level which, once aggregated, yields the system-wide volume of other operational and non-material conduct losses.

1.1 Frequency modelling: Negative Binomial distribution

The modelling of frequency aims at determining the most appropriate distribution of the number of annual operational losses. The reason for choosing Negative Binomial, in a departure from the Poisson distribution commonly used to model frequency, is based on empirical evidence. This is reinforced by the fact that the Poisson distribution has a single parameter, the mean, which is also the variance (Krishnamoorthy, 2006). Therefore, applying the Poisson distribution to the number of losses would limit the capacity to modulate the shock to an undesirable extent in the context of a stress test. Negative Binomial and Poisson distributions[73] are featured in Chart 8.1 against real data.

Chart 8.1

Cumulative Distribution Functions



Notes: the estimates are illustrative only, based on the number of other operational risk losses experienced by a bank chosen randomly for a given amount bucket. The x-axis represents the number of annual losses, using a five-year track record. The minimum and maximum (green vertical lines) and the average annual number of losses in this category (light blue line) are deducted from this track record.

Empirical evidence shows that the preferred Negative Binomial distribution displays the relevant variance for stress test purposes: it covers the whole range of historical data, i.e. the annual number of losses incurred in the past five years (the space between the two green vertical lines in the example shown in Chart 8.1), whereas the Poisson distribution exhibits a high degree of concentration around the mean.

[73] Poisson distribution is parameterised using the mean of the empirical data.

Regardless of the percentile chosen, applying the Poisson distribution to model the frequency of losses would imply overly rigid outcomes of Monte Carlo simulations.

To fit the Negative Binomial distribution, the two parameters, p and r (Krishnamoorthy, 2006), are calculated using the arithmetic moments matching method (Wasserman, 2004) in the following way:

$$p_{b,i,r} = \frac{\mu_{b,i,r}}{\sigma^2_{b,i,r}}$$

$$r_{b,i,r} = \frac{\mu^2_{b,i,r}}{\sigma^2_{b,i,r} - \mu_{b,i,r}}$$

where μ, the mean, is derived from the banks' reporting,

σ, the standard deviation, is derived from the banks' reporting,

b stands for the buckets with b_j the bucket displaying the total amount of losses in the interval j,

i stands for the institution, and

r, the risk type, can be either r_{nmc} for non-material conduct risk or r_{oor} for other operational risk.

1.2 Severity modelling

The lognormal distribution is a standard distribution used in modelling the severity of losses, which is recommended in BCBS (2011). It factors in two parameters, the mean μ and standard deviation σ (Krishnamoorthy, 2006). They are estimated by the method of arithmetic moments matching (Wasserman, 2004), also using the variance derived from the Austrian loss data collection. As such, it is assumed that the variance of Austrian losses is comparable to the losses within the sample of banks in the stress test exercise (assumption of substitutability).

The two key parameters read as follows:

$$\mu = \log\left(\frac{m^2}{\sqrt{(v + m^2)}}\right)$$

$$\sigma = \sqrt{\log\left(\frac{v}{m^2} + 1\right)}$$

m, the mean, is derived from the banks' reporting, whereas v, the variance, is derived from granular Austrian data. Given that distributions are calculated at the level of each bucket, for both non-material conduct losses and other operational losses, the lognormal distribution parameters can therefore be estimated for a given bank i in bucket b for risk type r as follows:

$$\mu_{i,b,r} = \log\left(\frac{m_{i,b,r}^2}{\sqrt{(v_{b,r} + m_{i,b,r}^2)}}\right)$$

$$\sigma_{i,b,r} = \sqrt{\log\left(\frac{v_{b,r}}{m_{i,b,r}^2} + 1\right)}$$

where b stands for the buckets with b_j the bucket displaying the total amount of losses in the interval j,

i stands for the institution, and

r, the risk type, can be either r_{nmc} for non-material conduct risk or r_{oor} for other operational risk.

1.3 Producing the aggregate loss distribution

The aggregate loss distribution is the distribution of annual loss outcomes. It results from the combination of frequency and severity distributions via Monte Carlo simulations (BCBS, 2011). The number of simulations, s, is set at a minimum of 100,000 for the model to produce stable results.[74] Distributions are estimated for each bank at bucket level, under the assumption of independence across buckets.

Table 8.2
Step-by-step process of the Monte Carlo simulations

Step 1	A random draw using the frequency distribution parameters yields one number of losses, which is used as an input to the severity distribution to return one annual loss outcome, at bucket level.
Step 2	Step 1 is reproduced for each bucket. The loss outcome for each bucket is summed to yield one annual loss outcome.
Step 3	Steps 1 and 2 are reproduced s times (the number of Monte Carlo simulations). As a result, s annual loss outcomes are obtained.
Step 4	The s annual loss outcomes form the Aggregate Loss Distribution. The 50th percentile value yields the loss projection in the baseline scenario, the 90th percentile the loss projection in the adverse scenario.

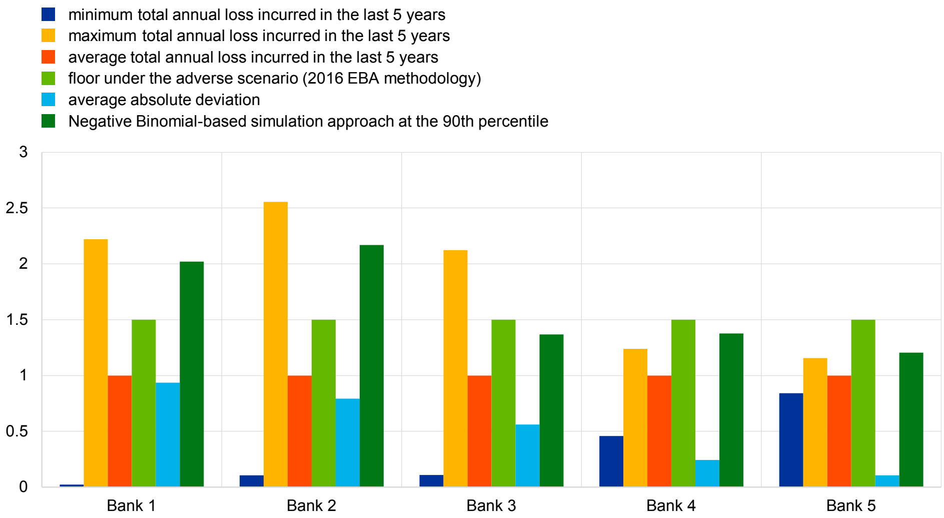
Chart 8.2 compares real data and projections for five representative banks from the EBA 2016 stress test sample.

[74] For the projection of losses, the number of 100,000 simulations has been found to yield stable results.

Chart 8.2

Comparison of empirical versus projected data

Other operational risk – adverse scenario



Notes: for each bank, the chart exhibits the minimum annual loss in the past five years, the maximum loss and the average, followed by the value of the floor in the 2016 EBA methodology (1.5 times the average) and the average absolute deviation. The last bar shows the projections estimated by the top-down model at the 90th percentile. All observations are normalised, using the average annual loss value.

In Chart 8.2 the banks are shown in decreasing order of average absolute deviation from the mean. There is a positive, though non-systematic, relationship between the average absolute deviation from the mean and the projected loss amount: the greater the variations in previous historical losses, the greater the loss projections relative to average historical losses. In the five cases shown in Chart 8.2, the projections are never above the maximum loss and in two cases are above the floor fixed at 1.5 times the average loss, under the 2016 EBA methodology. These two banks, 1 and 2, are also the banks with the highest average absolute deviation from the mean. The top-down approach to operational losses successfully factors in higher variance in individual past losses via the standard deviation used as an input of the frequency distribution.

2 Capital requirements

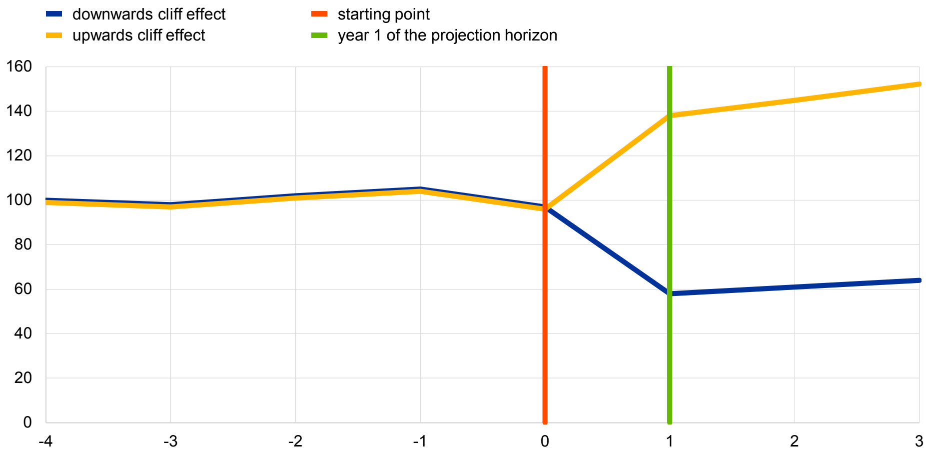
The degree of flexibility of a top-down operational risk model is a key conceptual question, i.e. whether such a model should be able to capture idiosyncrasies in the way banks calculate their own capital requirements or if it should apply regardless of individual banks' own modelling. Indeed, under the advanced measurement approach (AMA) institutions display significant model variability, i.e. the same data can yield significantly different results across institutions. The building of a "one-size-fits-all" AMA model is, therefore, quite challenging. The chosen alternative solution is to apply the growth rate estimated in a top-down manner to the risk exposure amount (REA) starting point.

Under the most advanced approach, capital requirements are estimated by banks assuming that annual operational losses would fall below the level of capital requirements at the 99.9th level of confidence. In that respect, banks are expected to combine several sources of loss information, including their own track record of losses. Given the high percentile sought, top-down modelling of operational risk capital requirements calls for a consistent approach in modelling the far tail of the loss distribution to reach the required high level of accuracy. It implies a significant number of Monte Carlo iterations (at least one million) to reach sufficient stability in the outcome.

Another reason why capital requirements are challenging to model from a top-down perspective is that it involves the replication of AMA models which vary significantly from one institution to another[75]. Such heterogeneity hinders the ability of a one-size-fits-all model to adequately capture idiosyncrasies. These idiosyncrasies may stem from the differing modelling assumptions used by the banks, but also from the individual track record of losses where a single material loss can materially influence the shape of the aggregate loss distribution and shift estimated capital requirements upwards. In this context, top-down projections applied right away in the projection horizon may lack the required accuracy, because of the cliff effect that would materialise (i.e. a sudden increase or decrease in capital requirements in the first year of the projection horizon, see Chart 8.3). A two-step approach therefore appears warranted, whereby a simulation approach is first used to calculate a growth rate which is then to be applied to the banks' starting point value.

Chart 8.3
The undesirable cliff effect in the projection horizon

Hypothetical situation where top-down projections are not anchored to the banks' starting points



The top-down model eventually projects capital requirements using losses projected in a top-down manner. For the purpose of the capital requirements calculation, loss

[75] The heterogeneity in the way banks model their capital requirements under the Advanced Measurement Approach is also a reason why the Basel Committee has envisaged reforming the advanced approach for operational risk.

frequency is fitted to a Poisson distribution, combined with a lognormal distribution for loss severity, in line with regulatory expectations (BCBS, 2011). Consequently, the top-down model estimates the rate of growth of capital requirements for each year of the projection horizon relative to the top-down estimate of capital requirements at the starting point. The projected growth rate is then applied to the bank's own starting point.

Frequency is modelled using the Poisson distribution. Its only parameter is estimated by the empirical average of the annual number of losses. The estimate of capital requirements in the projection horizon takes due account of losses projected in a top-down manner, e.g. losses projected in years 1, 2 and 3 of the projection horizon are used as an input to estimate capital requirements in year 3.[76] Similarly, the projection of capital requirements in year 2 uses past losses as an input, complemented by losses projected in a top-down manner for years 1 and 2. Loss projections are therefore progressively phased in in the track record of losses used for modelling capital requirements in the projection horizon. However, the material conduct risk losses used for the purpose of the top-down capital requirements calculation are the bottom-up values, in the absence of a top-down approach to model this subcategory of losses. Severity is modelled using the same distribution as for the P&L projections, i.e. lognormal distribution. The structure of the Monte Carlo simulations is in line with the description in Table 8.2, apart from the number of simulations and the percentile chosen. As capital requirements are estimated using the 99.9th percentile, this implies a greater number of simulations, at or above 1 million per bucket.

The estimation of top-down capital requirements is then adjusted using the institution's starting point as a reference:

$$pREA_y = REA_{2015} \times \frac{eREA_y}{eREA_{2015}}$$

where y is the year of the projection horizon,

REA is the actual risk exposure amount,

$pREA$ is the projected risk exposure amount (the top-down final value), and

$eREA$ stands for the estimated risk exposure amount (estimated according to the loss distribution approach detailed above).

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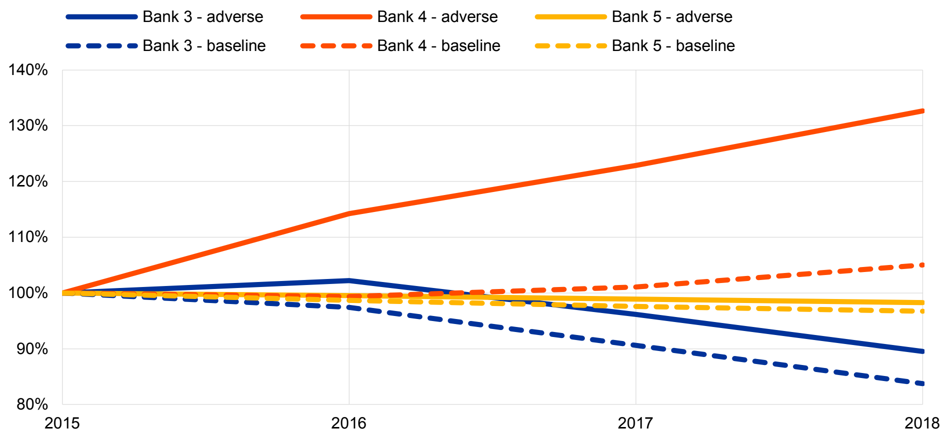
76 In the projection horizon, projections are broken down into buckets based on historical breakdown proportions.

Chart 8.4

Projection of growth rate of capital requirements in a sample of three banks



For illustrative purposes, the capital requirements modelling approach is applied to the previous sample, excluding Banks 1 and 2, which are not under AMA[77]. In the adverse scenario, the situations are heterogeneous. Banks 3 and 5 reveal a decrease in capital requirements under the adverse scenario, although lower than in the baseline. The reasons are idiosyncratic: Bank 3 experienced material losses in the past, and losses projected under the adverse scenario are lower in magnitude than historical losses, while Bank 5 is partially under the simpler approaches, which shifts the overall top-down projections downwards. Heterogeneity in the results is due to structural causes, dependent at bank level on the regulatory approach and on the past material conduct losses versus the losses projected in the same category. Under the simpler regulatory approaches, the capital requirements in the adverse scenario decrease mechanically, due to the deterioration of the economic environment having a downward impact on the Relevant Indicator. Under the AMA, capital requirements may increase, due to the possibly material projected losses flowing into the track record of losses. However, if a bank under AMA has experienced material conduct losses in the past that are greater in amount than the losses projected, then the capital requirements may also decrease. As such, the balance between simpler approaches and AMA, together with the balance between past and projected losses, conditions to a certain extent the top-down estimates of bank-level capital requirements.

3 Conclusion

The new operational risk module presented above has been successfully incorporated in the top-down toolkit, and was first in operation during the 2016 EBA

[77] Capital requirements of banks under the simpler approaches are also modelled from a top-down perspective, in line with the regulatory provisions that automatically link capital requirements to the Relevant Indicator, see Article 316 of the Capital Requirements Regulation (2013) for a detailed definition.

stress test exercise, in which it served as a powerful quality-assurance tool.[78] The module has acquired sufficient maturity to be implemented as a standalone computational tool in macroprudential exercises.

In terms of future enhancements, the inclusion of top-down projections for material conduct risk losses is currently being investigated. These losses are challenging to estimate from a top-down perspective due to, among other reasons, the absence of up-to-date transparent information on cases pending settlement. The distribution of these losses, with heavy tails and possibly long-term impacts on the banks' balance sheets, makes banks' solvency even more sensitive to the modelling outcome. Additionally, the recent possible change in regime in the amount of losses represents another challenge, in terms of data availability. Indeed, operational losses have progressively increased following the 2007-08 crisis, reaching a cumulative total of €200 billion worldwide from 2009 to 2014 (ESRB, 2015). This intensification is attributed, among other reasons, to the increased economic activity prior to the crisis, linked to volatility during the crisis which made mis-selling activities visible. Data from before the crisis should not be used without being appropriately converted, thus limiting the historical reach of the database. However, some business models and geographical locations seem more likely to attract material conduct losses. Such dependencies, conditional on statistical robustness, may allow for a modelling approach leading to material conduct losses projections that will enrich the top-down toolkit in the future. This framework would also allow, as an alternative, the modelling of the dissemination into the banking system of an overall conduct cost, projected ex ante at system-wide level.

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[78] The tool is MATLAB-based and purpose-built as a standalone model so that its highly demanding computational requirements, in particular due to the extensive use of Monte Carlo simulations, do not destabilise the whole top-down infrastructure.

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Chapter 9 Loan flow satellite models

By Marco Gross and Fabrizio Venditti

This chapter presents the satellite models for bank loan volumes, based on which the bank loan flow paths can be derived conditional on some macro-financial scenarios. The models and their projections can be employed in a dynamic balance sheet application in which banks are allowed to adjust their balance sheet size and composition in line with developments in the macro-financial scenario. Such dynamic balance sheet modelling is essential for any macroprudential assessment, because macroprudential policy is precisely meant to affect the economy via price and volume changes at the bank level (see also Chapters 3 and 11).

To develop the loan flow models, the same Bayesian model averaging methodology has been employed that was used to develop various other satellite model components presented in this book (see for example Chapters 4 and 5).The models cover three portfolio segments across the 28 EU countries.

1 The relationship between loan flows, stocks and economic activity flows

The aim is to model bank loan flows, specifically flows of new business, as a function of macro-financial variables. This focus on new loan flows is justified on economic and methodological grounds. To the extent that spending is financed by credit, in a given period consumption and investment will reflect the new lending that is extended in that period (to the extent it was financed by new credit). Since GDP is a flow concept, the growth rate of GDP should be related to the growth rate of the credit flow rather than to changes in credit stock. Biggs et al. (2009) develop a simple theoretical model that clarifies this point and shows that consumption and investment flows in the economy are related to new lending rather than to the stock of loans. If the nature of this relationship is not properly taken into account, some puzzling results might emerge. The literature on financial crises, moreover, documents that recoveries following a financial crisis are typically "credit-less", in that GDP (flows) recover while the stock of credit is high before falling again.[79] This apparent puzzle, referred to as the "Phoenix Miracle", simply disappears when post-crisis recoveries are analysed by comparing GDP flows with credit flows rather than with credit stocks[80], i.e. "credit-less" recoveries only appear to be credit-less because the stock of credit is related to GDP (a flow concept).

Having clarified the economic rationale, to the extent that the change in the stock of credit equals new loans, double differencing the stock of loans should give us the

[79] As a useful entry point to the literature in this respect see for example Calvo et al. (2006), Claessens et al. (2009) and Calvo et al. (2010).

[80] See http://voxeu.org/article/myth-phoenix-miracle

variable of interest. However, an additional caveat applies, as changes in the stock of loans recorded in banks' balance sheets may reflect factors that are not directly related to economic developments but rather to changes in accounting methodologies or bank-specific decisions. This could contaminate the data making it hard to uncover meaningful correlations between credit changes derived from loan stocks and the macroeconomic variables.

A useful decomposition of the change in loan stock at the bank level into components that are likely to be impacted by macroeconomic shocks and other factors is as follows:

$$L_t = \mathrm{P}_{\mathrm{t}-1}(1 - \mathrm{r}_{\mathrm{t}}) + \mathrm{NB}_{\mathrm{t}} + \mathrm{NPL}_{\mathrm{t}-1}(1 - \mathrm{w}_{\mathrm{t}}) + \Delta Valuation_t + \Delta Classifications_t + \varepsilon_t$$

P and NPL denote, respectively, the performing and non-performing portion of the gross loans stock L. The parameters r and w denote a maturity/repayment parameter and NPL write-off rate respectively.

The equation clarifies that, while new business flows (NB_t) reflect consumption and investment choices and are therefore to be linked to the stress test scenarios, write-offs (w_t), changes in the valuation of securities and repos ($\Delta Valuation_t$), changes in the classification of some items ($\Delta Classifications_t$) and other factors collected in the residual ε_t (reflecting, for example, changes in group classification) all contaminate the relationship between changes in the stock of gross loans and macroeconomic factors. Modelling these factors is beyond the scope of the book.

1.1 Data

The ECB's monetary financial institution (MFI) interest rate (MIR) and volume statistics for new business flows form the basis for the models. The aggregates for three portfolio segments are employed for non-financial corporate exposures, household mortgages and consumer credit. The loan flows of new business have a monthly frequency, at which they are seasonally adjusted and then summed to obtain within-quarter flows.[81] The time series cover 24 EU countries (all of the European Union excluding Denmark, Croatia, Sweden and the United Kingdom).[82] For non-euro area EU countries, the models are based on sums of loan exposures in local currency and in euro (where the latter is significant). For the vast majority of cases across countries and portfolio segments, the series start in the first quarter of 2003, comprise up to 52 observations and run to the current end-sample ending in the fourth quarter of 2015.

Since the models are based on country-level MIR data, they can be referred to as being "macro-sectoral" in nature, i.e. capturing country-level relationships in the first instance. The projections obtained from the models are subsequently being attached

81 The seasonal adjustment has been conducted using an X-13 ARIMA-Seats quarterly seasonal adjustment method.

82 For the consumer credit segment, the series for Poland is also missing. For Croatia, data series are available but are deemed too short to be useful for modelling purposes.

to bank-specific starting point. More specifically, bank-specific data for new business flows as of 2015 constitute the starting point for the projections that then drive new business loan flows across banks within the same country/portfolio.[83] As for all other risk parameters, the new business flow paths will be applied at country exposure level, meaning that, for example, the German corporate exposure (or here new business flow) of an Austrian bank will be projected by attaching the percentage changes of new business from the model for German corporate flows.

1.2 Econometric model approach and model results

As for all other major risk categories, in particular for credit risk and bank interest rate spread models to determine the NII trajectories of banks (see Chapters 4 and 5), the loan flow models are developed based on the Bayesian model averaging (BMA) technique. The individual equations in a model space for any one dependent variable are subject to a set of sign restrictions that are imposed on the long-run multipliers (LRMs) of the predictor variables. Table 9.1 summarises the sign constraints that can be imposed on the potential predictor variables in the respective loan flow portfolio segments.

Table 9.1

Predictor inclusion settings and sign constraints

	Real GDP	Real private consumption	Real investment	Real exports	Unemployment rates	Consumer prices	Residential property prices (Y1, Y2, Y3)	Sovereign bond yield spread	Short-term interest rate
CORP	1		1	1		1		-1	-1
HH-HP	1	1			-1	1	1	-1	-1
HH-CC	1	1			-1	1		-1	-1

Notes: A ‘1’ or ‘-1’ means that the predictor variables were allowed to appear in the model equations for a dependent variable that are listed in the first column of the table, with the ‘1’ and ‘-1’ indicating a positive and negative sign on the long-run multiplier of the predictor, respectively. No entry in the table means that the predictor variable was excluded a priori.

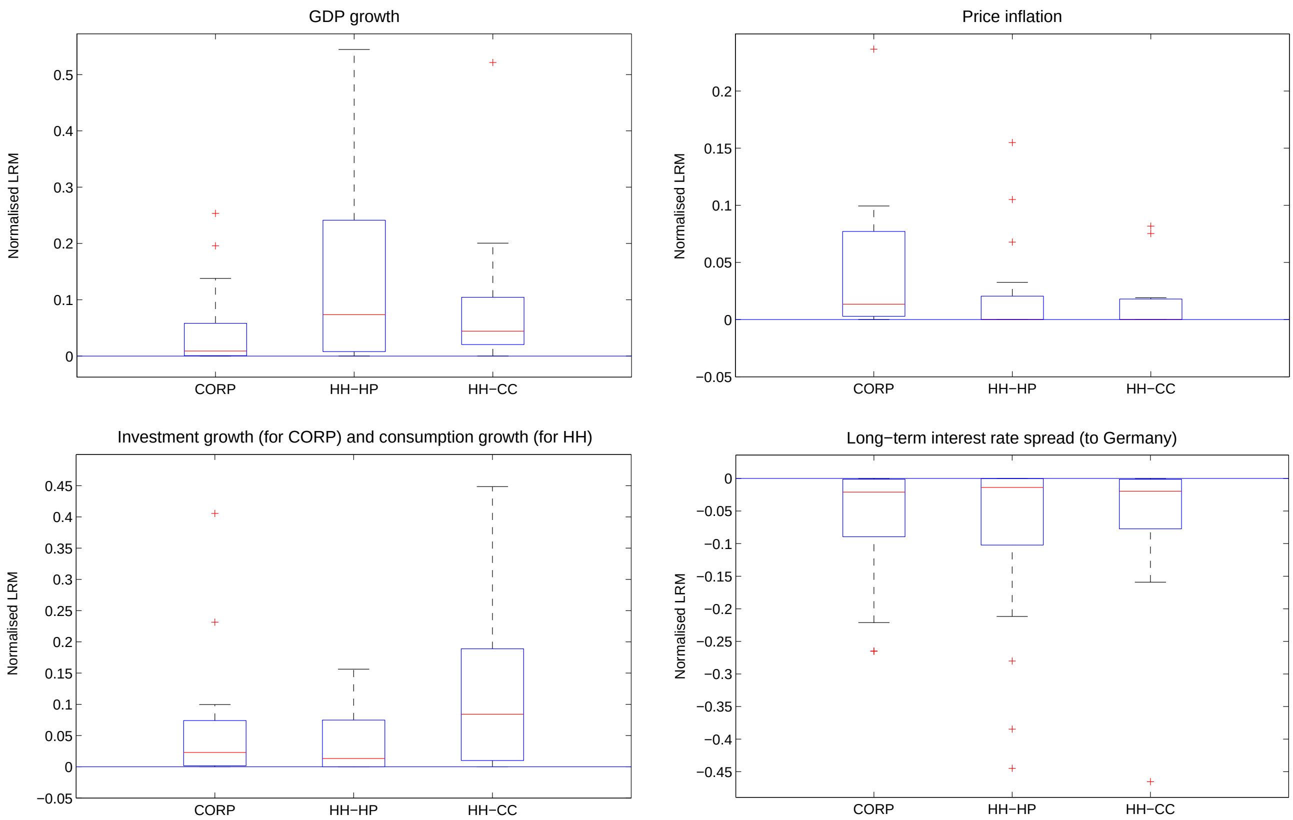
Chart 9.1 shows the cross-country distributions of the normalised LRMs based on the sample of 28 EU economies for the three portfolio segments, for five of the nine model variables (the third figure embedded in Chart 9.1 contains the investment growth multiples for the corporate segment along with the private consumption growth N-LRMs for the two household segments).

[83] Such data has been made available through the EBA/ECB stress test template collections from the banks in the 2014 and 2016 stress tests.

Chart 9.1

Normalised long-run multiplier (N-LRM) distribution on selected macro-financial predictor variables in the loan flow models

(multiples of standard deviations)



Notes: The box plots visualise the cross-country (cross-model) distribution of the normalised long-run multipliers (LRMs) linking the loan flow log differences at country and segment level with the predictor variables indicated in the header of the charts. An LRM is defined as the sum of the coefficients on the contemporaneous and lagged coefficients of a given predictor variable. The LRMs are normalised by multiplying the initial LRM estimates by the ratio of the standard deviation of the predictor variable and the standard deviation of the dependent variable.

With respect to GDP growth, for instance, one can observe a more pronounced relationship between loan flows and real activity in the household mortgage segment, while for price inflation, the link for the corporate loan flows appears to be somewhat more significant (although the N-LRMs on inflation are generally smaller in magnitude).

1.3 Attaching country/portfolio segment-level loan flows to bank starting point loan flows

The attachment of the loan flow trajectories derived at country/portfolio segment-level to a bank-specific starting point entails the following steps. The log difference-based annual loan flow paths at the country and portfolio levels are linked to a bank's new business starting point in the first year and, subsequently, for the second and third year, by chaining the new business volumes to the previous year's projections. That is,

$$flow_{t+1} = \exp(\ln(flow_t) + f_{t+1}),$$

where f_{t+1} is a projected annual log percentage change for the flow out of the BMA model for a given country and segment.

Along with additional scenario assumptions for write-off rates, the new business flow trajectories then imply a gross loan growth profile at both the bank and the country/portfolio segment level, which is implied by the various processes and assumptions.

2 Illustrative scenario-conditional loan flow forecasts

Once estimated for the various segments and across countries, the posterior loan flow models can be used to produce conditional mean and density forecasts of the loan flows over a scenario horizon, as a function of some underlying macro-financial scenario. For the countries and portfolio segments for which the historical loan flows were either missing or insufficient to develop a robust satellite model, the approach that is employed to derive the scenario-conditional loan flow paths is again to translate the scenarios for the missing countries using the models available for the other countries in the same segment; it is an approach that in the previous chapters was introduced and referred to as "cross-filling". For example, for the consumer credit segment for Poland, no model is available. The "cross-filling" approach entails the feeding of the scenario for Poland through all the other country models that are available for the consumer credit portfolio. From the resulting multi-model forward paths for Poland, one can take the median to arrive at a scenario-conditional path for the consumer loan flows for Poland.

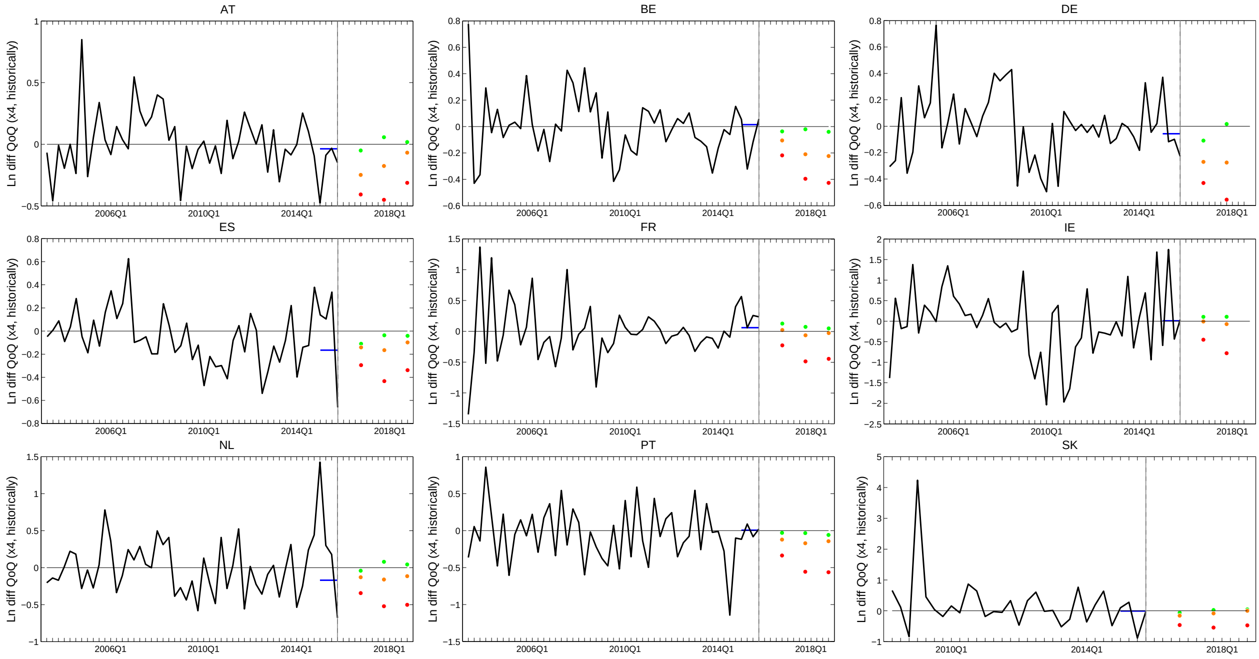
As an illustration, the loan flow forecasts were derived conditional on a baseline and an adverse scenario that are very similar in shape across macro-financial variables and countries compared with the scenario employed for the 2016 EBA stress test exercise. The figures embedded in Chart 9.2 represent a subset of the EU countries and are shown here only for the corporate segment.

For some countries the loan flow changes appear to be quite sizeable at first glance; it is useful to see these trajectories in a historical perspective, however, where the significant variance becomes apparent and against which the variation in the forward paths is justified. It should also be borne in mind that gross loan stocks and their changes along the scenario horizon will not be as significant as the new business changes here since new business constitutes a relatively small portion relative to outstanding stocks.

Chart 9.2

Illustrative corporate loan flow forecasts conditional on an exemplary baseline and adverse scenario

(annualised log differences historically; annual log differences during the scenario horizon (2016-18); green for baseline, orange for adverse median; red for adverse 25th percentile)



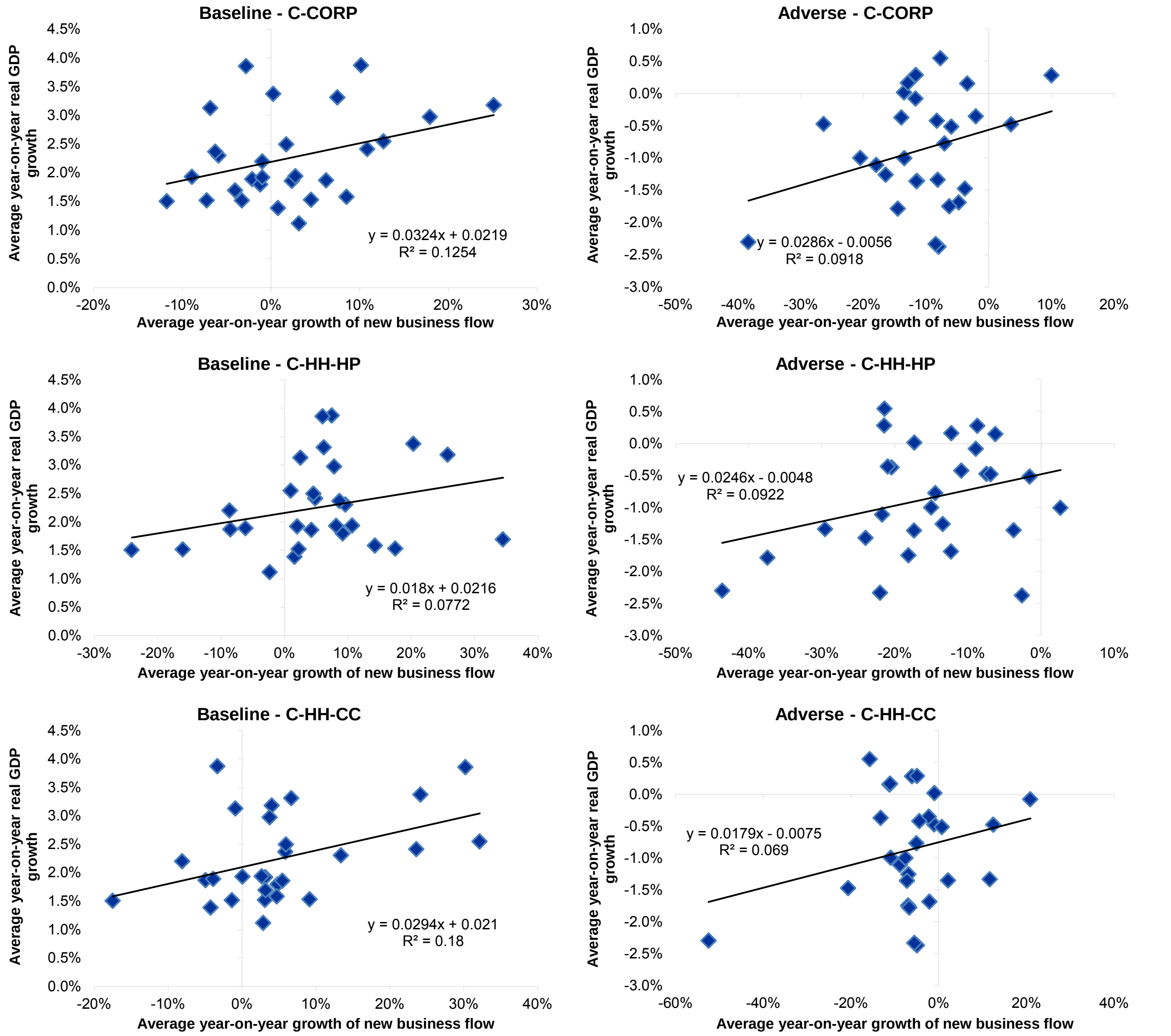
Notes: A collection of plots is embedded in this chart for some selected countries, depicting the historical evolution of quarter-on-quarter log percentage growth of new business flows (annualised) along with the scenario-conditional forecasts. There is a blue line included in all charts, spanning the first quarter to the fourth quarter of 2015, which reflects the log percentage change of the sum of the flows in 2015 over the sum of flows in 2014. The scenario paths have that same format, i.e. represent year-on-year log percentage changes of the sum of the flows within the years (i.e. involving the sum of the projected quarterly flows from the models). For the adverse scenario, there are two trajectories presented in the charts; one reflecting the median and the other the 25th percentile of the underlying scenario-conditional density forecasts of the loan flows. The 25th percentile paths are also shown to depict the uncertainty underlying the projections.

For the adverse scenario, Chart 9.2 also shows the adverse conditional 25th percentile besides the conditional mean, to depict the uncertainty that surrounds the projections. The uncertainty results here from three combined sources: coefficient uncertainty, residual uncertainty, and model uncertainty, which is captured through the use of the BMA methodology.

As an additional means to examine the loan flow model projections, Chart 9.3 presents an assessment of how the loan flow changes (horizon averages from the paths as shown in Chart 9.2) correlate ex post with average GDP growth trajectories along the scenario horizon, here covering all three portfolio segments and all EU model countries. The relationship is visibly positive in all cases. One would not need to expect an overly strong relationship as GDP is, of course, not the only determinant of the loan flow projections, as numerous other predictor variables are involved in the models. It is useful, nonetheless, to see a positive relationship with GDP as a key indicator of the country-specific scenario characteristics.

Chart 9.3

Real GDP growth versus growth in new business flows



Notes: C-CORP = non-financial corporate; C-HH-HP = household mortgage segment; C-HH-CC = consumer credit. The averages are over the three years of the scenario horizon for both real GDP and the loan flows.

For a short description of how the new business loan flow paths are used in conjunction with the scenario-conditional probabilities of default (and some other related parameters) to derive the performing and non-performing loan path trajectories of the banks, see Section 1 of Chapter 4 (“Credit risk satellite models”).

3 Conclusions

This chapter presented the loan flow satellite model system, whose role is to derive the new business loan flow trajectories across countries and different loan portfolio segments, conditional on a given assumed macro-financial scenario.[84] Being in a position to derive the scenario-consistent paths for loan flows is crucial, in particular, for a dynamic balance sheet application of the stress test apparatus. From the perspective of a macroprudential policy assessment, it is also of crucial importance to have models that allow the derivation of robust and reliable (policy) scenario-conditional forward paths for volumes, as well as prices (see Chapter 5 and the discussion on bank interest rates). For instance, capital-based macroprudential policy instruments are meant to exert their impact through bank funding cost changes and a pass-through to loan interest rates, that eventually affect loan volumes. Loan flow models are valuable not only to align supply and demand in line with historical regularities, but also to estimate how banks actively manage assets and liabilities under stress.

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[84] In addition to the loan flow-based models presented in this chapter, there is a separate satellite model system based on growth of credit stocks (not presented in this chapter), which serves as a useful benchmark for the loan stock paths implied by loan flows and the additional assumptions (as hinted at in Section 3).

ESTIMATING MACROECONOMIC FEEDBACK

Chapter 10 Estimating the macroeconomic feedback effects of macroprudential measures – Dynamic Stochastic General Equilibrium (DSGE) models

By Elena Rancoita and Björn Hilberg

In an economy, banks play an important role in financing the investment opportunities of firms and the consumption of households. To avoid excessive credit creation and risk-taking behaviour by banks, minimum capital requirements are introduced to link the credit creation of a bank to its solvency. In an adverse scenario, banks might pre-emptively raise their capital buffers by, for example, deleveraging, issuing equities or changing their portfolio allocation in order to avoid negative effects on their solvency. The banks' response to an adverse scenario creates second-round effects on the macroeconomic environment and, hence, amplifies the impact of the shocks that initially hit only the banking sector.

The quantification of second-round effects on the real economy requires models with real-financial linkages. One possibility is to analyse the feedback effects between macroeconomic and financial variables using Dynamic Stochastic General Equilibrium (DSGE) models, which are microfounded models based on the assumption that agents optimise their utility function. DSGE models are regularly employed at the ECB for macroprudential policy analysis, for example, to assess and compare different types of macroprudential policies. In the stress test framework, DSGE models are used to assess second-round effects on the real economy, assuming that banks would respond to the macroeconomic scenario by adjusting upfront their capital ratio. They complement other tools that are employed for that purpose, possibly using micro data (see, for example, Chapter 11).

An advantage of using large-scale DSGE models is that they are particularly suited to simulations and can quantify the effects of policies based on precise assumptions about agents' behaviour. A second advantage of employing DSGE models for policy analysis of the euro area is the fact that their calibration does not require the amount of data needed to estimate econometric models and to identify shocks. DSGE models can be used, for example, as a thought experiment, assuming steady-state values which are not necessarily taken from a long time series. The two main limitations of the DSGE models currently used for macroprudential policy analysis are that banks are assumed to have a very simplified balance sheet and that there is no choice between issuing equities and deleveraging. Changes in the business models and linkages with the shadow banking sectors are also potential fields of expansion in this literature which have not yet been explored. This would also complement other attempts using micro data, such as agent-based models.

The rest of this chapter presents the DSGE models developed by ECB staff and illustrates their potential use in macroprudential policy analysis. In Section 1, the theoretical model is described, while Section 2 deals with the calibration of the DSGE models. Sections 3 and 4, respectively, illustrate theoretically and empirically some examples of policy analysis conducted with the large-scale DSGE models described in Section 1. Section 4 also explains how the DSGE model has been used in the context of the macroprudential extension of the EBA stress test 2016 (see Chapter 3).[85]

1 Model description

Two DSGE models are currently used at the ECB to quantify the impact of macroprudential policies and shocks in the banking sector on the real economy: Darracq Pariès et al. (2011) and Darracq Pariès et al. (2015). This chapter focuses on the first model, as this is the model used for the analysis of the macroprudential extension of the EBA 2016 stress test exercise. In Darracq Pariès et al. (2011), the economy consists of three agents: households, entrepreneurs and banks. Firms are active in two sectors producing residential and non-residential goods, respectively. Monetary policy is formalised in terms of an interest rate rule that prescribes a response to inflation, output growth and asset prices.

Banks are affected by three layers of financial frictions, which have important implications for the propagation of shocks in the economy. First, banks face risk-sensitive capital requirements as well as adjustment costs related to their capital structure. Second, banks have some degree of market power in the retail market which generates imperfect pass-through of market rates to bank deposit and lending rates. Third, due to banks' imperfect information about their borrowers and hence monitoring costs on their credit contracts, firms and impatient households face an external financing premium which depends on their leverage. Macroprudential measures are modelled as external shocks to the banking (e.g. system-wide and sectoral capital requirements) or households (e.g. loan-to-value ratio caps) sectors. A complete representation of the model can be seen in Chart 10.1.

1.1 Households

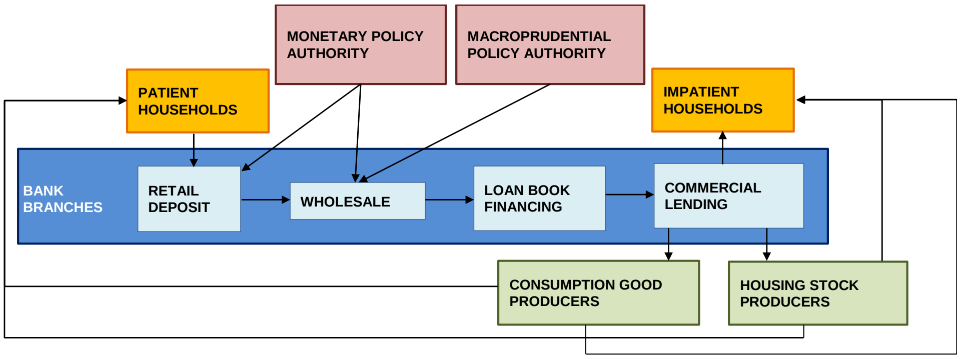
The economy is populated by two types of households which differ in their propensity to save, modelled by a different discount factor.

Patient households are the equilibrium net lenders in the economy and, thus, the owners of the capital and housing stock firms as well as banks.

[85] See also ECB (2016).

Chart 10.1

Schematic representation of Darracq et al. (2011)



While patient households save in the form of one-period real deposits, impatient households borrow funds from banks in order to purchase houses. Hence, impatient households agree with banks on one-period state-contingent debt contracts and pay a fixed nominal lending rate on the loan amount. Unlike in the case of patient households, both the income and housing stock value of impatient households are subject to common idiosyncratic shocks. If the idiosyncratic shock is too adverse, a household cannot repay the loan and therefore defaults. In this case, commercial banks can seize borrowers' collateral at a certain cost as in the framework of Bernanke, Gertler and Gilchrist (1999). The loan amount is restricted by a borrowing constraint expressed in terms of a loan-to-value ratio.

1.2 Production sectors

Entrepreneurs produce housing and wholesale intermediate goods and are in perfect competition. Residential goods are treated as durable goods and serve two purposes: they can be either directly consumed or used as collateral in the mortgage market. Analogously to impatient households, entrepreneurs borrow from the banking sector and for this reason engage in one-period state-contingent debt contracts with banks. If the shocks to an entrepreneur's income and capital stock values exceed an endogenously determined threshold, entrepreneurs default on their debt and the bank can seize the capital stock used to produce residential and non-residential intermediate goods. In order to prevent severe losses, the loan amount is restricted by a borrowing constraint expressed in terms of a loan-to-value ratio.

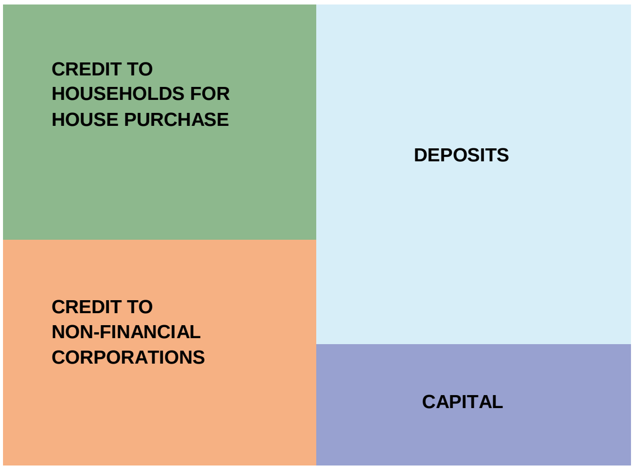
1.3 Banking sector

The banking sector is owned by patient households and consists of banking groups which are segmented in several branches in order to make their optimisation problem more tractable. Following Gerali et al. (2010), each banking group is first composed of a wholesale, deposit and loan book and two commercial lending branches.

The wholesale branch obtains financing in the money market and allocates funds to the rest of the group, facing an adjustment cost to the overall capital ratio of the group. The wholesale branch operates under perfect competition, taking the bank capital as given, and decides on the amount of deposits to be received and on the loans to non-financial corporations and households to be granted. Its balance sheet is represented below in Chart 10.2. As can be observed in Chart 10.2, the bank's balance sheet is rather stylised and banks do not decide endogenously on the amount of equity raised. On the contrary, the capital stock is accumulated out of retained earnings.

Chart 10.2

Representation of a wholesale bank's balance sheet



The second segment of the banking group includes a deposit branch and two loan book financing branches. The former collects savings from patient households and places them in the money markets, while the latter receive funding from the wholesale branch and allocate it to the commercial lending branches. In contrast to the wholesale branch, the second segment operates under monopolistic competition and faces nominal rigidities when setting interest rates. Retail deposit branches and loan book financing branches are monopolistic competitors and, in each period, face constant probability of being able to adjust the nominal interest rate on deposits and loans (see Calvo, 1983). The deposit and the loan book financing branches generate the lending spread in the model.

The third segment of the banking group is formed by two commercial lending branches which provide loan contracts to impatient households and entrepreneurs. Owing to banks' imperfect information about their borrowers and hence the costs of monitoring their credit contracts, firms and impatient households face external financing premia which depend on their leverage.

1.4 Monetary, fiscal and macroprudential authorities

The government finances public spending with lump-sum transfers. Monetary policy is specified in terms of an interest rate rule targeting inflation, output and their first difference as well as changes in the relative price of housing. The macroprudential policy rule is not specified within the model, but changes of macroprudential policy stance are modelled as exogenous shocks to the banking sector (e.g. via the banks' steady-state capital ratio or to the banks' steady-state risk weights) or to households' and entrepreneurs' borrowing constraints (e.g. loan-to-value capital ratio caps).

1.5 Multi-country model

A two-country version of the model has been developed in the ECB (see Darracq Pariès et al., 2015), which also allows for the assessment of complementarities between macroprudential and monetary policies in a financially integrated monetary union. This model explores the potential benefits of tailoring macroprudential policies to national circumstances while taking account of the single monetary policy stance. Individual economies are modelled following Darracq Pariès et al. (2011). In this model, the home country represents one country of the euro area and the foreign country represents the aggregation of the other euro area member states. The model was calibrated five times so that the home country was calibrated on one of the five largest euro area economies (Germany, France, Italy, Spain and the Netherlands) each time. The two countries are interconnected via trade and banking sector linkages. On the trade side, residential goods are treated as durable goods and are non-tradable, while non-residential goods can be traded across countries. With regard to cross-border credit linkages, it is assumed that households and firms can borrow abroad (as well as at home). The rest of the chapter is focused on the one-country model as it is the model currently used in the macroprudential extension of the stress test (see Chapter 3).

2 Calibration

Darracq Pariès et al. (2011) and Darracq Pariès et al. (2015) are calibrated to capture the banking system characteristics and macroeconomic features of each euro area country. The cross-country heterogeneity is reflected first through the degree of demand-side and supply-side credit frictions related to: (i) leverage and the credit risk profile of households and firms (e.g. PDs, LGs and indebtedness); (ii) the lending rate pass-through; and (iii) the bank capital channel (e.g. capital ratio and risk weights).

Households' indebtedness is an important structural factor determining how the economy reacts to, for instance, house price shocks. For this purpose, country-specific historical averages of loan-to-GDP ratios for households (data from ECB and Eurostat) were used to calibrate the degree of private indebtedness at the country level.

For the calibration of the banking sector, proprietary granular bank-level stress-test data from the ECB's comprehensive assessment is used inter alia to set credit risk characteristics (i.e. portfolio-specific probabilities of default or PDs and loss given default or LGD) determining the lending rates. Individual bank information is aggregated up to country-level indicators, also taking into account the geographical breakdown of banks' exposures. Bank capital adjustment costs are calibrated, based on stress-test data, on exposures and capital that is used to compute the target capital ratio at the country level. Country-specific bank interest rate pass-through estimates are used to calibrate the degree of stickiness in retail interest rates across countries. This affects the strength with which shocks to bank balance sheets spread to the real economy via the cost of bank financing. Households' indebtedness is an important structural factor determining how the economy reacts to, for instance, house price shocks. For this purpose, country-specific historical averages of loan-to-GDP ratios for households (sources: ECB and Eurostat) are used to calibrate the degree of private indebtedness at the country level.

3 Propagation of shocks to the real economy via or from the banking sector

This section describes the key transmission mechanisms of shocks to the real economy which are exogenous to the banking sector and also explains shocks which can arise from the banking sector. The next section illustrates how these shocks can be used for the impact assessment of macroprudential policies.

Banks are affected by financial frictions, which have important implications for the propagation of shocks from the banking sector to the real economy. Shocks can originate from the banking sector, for example due to changes in regulations or capital requirements. Similarly, shocks originating outside the banking sector can be amplified by banks, for example, after a sudden change in the propensity to default of households or entrepreneurs. The model allows for four types of shock to the banking sector: (i) a shock to the amount of capital of the wholesale branch (Section 3.1); (ii) a shock to the capital ratio target of banks (Section 3.2); (iii) a shock to the interest rate mark-ups of the loan book financing branches (Section 3.3); (iv) a shock to the sectoral risk weights (Section 3.4). Each branch of the banking sector contributes to the transmission of shocks to the real economy.

3.1 Shock to the amount of capital of the wholesale branch

To understand the transmission mechanism of shocks from the banking sector to the real economy, let us start by considering the objective function of wholesale branches (see equation 1). Variables related to wholesale branches are indexed by wb. When deciding on deposits (Dep_t^{wb}) and loans ($B_{HH,t}^{wb}, B_{E,t}^{wb}$), wholesale branches face risk-sensitive capital requirements as well as adjustment costs related to their capital structure, which is reflected in the objective function of a wholesale branch:

$$\max_{B_{HH,t}^{wb}, B_{E,t}^{wb}, Dep_t^{w}} R_{HH,t}^{wb} B_{HH,t}^{wb} + R_{E,t}^{wb} B_{E,t}^{wb} - R_t Dep_t^{wb} - \frac{\chi_{wb}}{2}\left(\frac{Bankcap_t}{RWA_{HH,t} + RWA_{E,t}} - e^{\varepsilon_t^{TCAP}} TCAP\right)^2 Bankcap_t \qquad (1),$$

where $TCAP$ is the target (steady-state) capital ratio of banks, χ_{wb} is a calibrated parameter, $Bankcap_t$ is the bank capital, $R_{HH,t}^{wb}$ and $R_{E,t}^{wb}$ are the gross interest rates of lending to households and entrepreneurs respectively, and $RWA_{HH,t}$ and $RWA_{E,t}$ are the risk-weighted assets of the exposures to the non-financial corporation and household sectors.

The capital ratio target and quadratic adjustment costs model the interactions between the banks' balance sheet structure, market discipline and the regulatory framework. On the one hand, a capital ratio above the regulatory requirements provides banks with a cushion against negative shocks to capital and thus reduces the risk of not being compliant with regulatory capital requirements, which may result in both monetary and reputational costs. On the other hand, bank capital is costly and banks are reluctant to maintain too large buffers, as this reduces profits.

From the wholesale branch maximisation problem, the following margins on loans to households ($R_{HH,t}^{wb} - R_t$) and entrepreneurs ($R_{E,t}^{wb} - R_t$) are obtained:

$$R_{i,t}^{wb} - R_t = \chi_{wb} \left(\frac{Bankcap_t}{RWA_{HH,t} + RWA_{E,t}} - e^{\varepsilon_t^{TCAP}} TCAP \right) \left(\frac{Bankcap_t}{RWA_{HH,t} + RWA_{E,t}} \right)^2 rw_{i,t} \quad i \,\epsilon \{E, HH\} \qquad (2)$$

The capital base of the wholesale branch increases over time due to the bank group's retained earnings (Π_t^b). The law of motion of bank capital can be described as:

$$Bankcap_t = e^{\varepsilon_t^{Bankcap}} (1 - \delta_{wb}) Bankcap_{t-1} + \upsilon^b \Pi_t^b \qquad (3),$$

where $\varepsilon_t^{Bankcap}$ is an exogenous i.i.d. shock to the capital stock and υ^b is the calibrated share of profits Π_t^b which is retained.

The model is used to assess the macroeconomic implications of an adverse shock to the bank capital position by assuming a negative value for $\varepsilon_t^{Bankcap}$. The bank capital shock results in an instantaneous increase in bank leverage. The deviation of the actual leverage ratio from the bank's target leverage ratio results in an increase in the loan-to-deposit margin charged by the wholesale branches for loans to households and entrepreneurs. This, in turn, results in lower loan demand which affects the amount of investment in the economy's fixed capital and housing stock. As a result, the production of residential and non-residential goods is reduced.

3.2 Shock to bank's capital ratio target

A shock to the capital ratio target (ε_t^{TCAP}) directly affects the adjustment cost function of bank's profit function (see equation (1)). A positive shock to bank's capital ratio target implies that a bank would deleverage and thereby increase the loan-to-deposit margin. Implicitly, deleveraging and the increase in the lending spread would lead to an automatic increase in bank capital via retained earnings. In reality, banks might also choose to increase capital by issuing new equities, but this is currently not obtained endogenously in the model.

3.3 Shock to sectoral risk weights

Risk weights play an important role in both the transmission and origination of shocks from the banking sector to the economy. Risk-weighted assets ($RWA_{i,t}$) are computed in the model following the Basel II formula:

$$RWA_{i,t} = e^{\varepsilon_t^{RW_i}} rw_{i,t} * B_{i,t}, \quad i \epsilon \{E, HH\} \tag{4}$$

$$rw_{i,t} = 12.5 * LGD_{i,t} PD_{i,t} \left\{ \Phi \left[(1 - \tau_{i,t})^{-0.5} \Phi^{-1} + \left(\frac{\tau_{i,t}}{1 - \tau_{i,t}} \right)^{0.5} \phi^{-1} 0.99 \right] - 1 \right\} \tag{5}$$

$$\tau_i = 0.12 \left[\frac{1 - \exp(-50 PD_{i,t})}{1 - \exp(-50)} \right] + 0.24 \left[1 - \frac{1 - \exp(-50 PD_{i,t})}{1 - \exp(-50)} \right], \tag{6}$$

Where $rw_{i,t}$ stands for risk weights, τ_i denotes the asset value correlation, $LGD_{i,t}$ is the loss given default, $PD_{i,t}$ is the probability of default, and Φ denotes the cumulative distribution function of a normal random variable.

This formulation of risk-weighted assets creates a dependency between bank solvency and the underlying scenario. Hence, in an adverse scenario, the probability of default of borrowers is expected to increase, leading to higher risk weights according to the Basel II formulation. This, in turn, would imply that banks would endogenously adjust either their capital or their lending in order to reach the steady-state capital ratio level. Given that the model does not allow for an endogenous decision to issue new capital, banks will endogenously reduce lending to the private sector, causing the macroeconomic conditions to deteriorate.[86]

Risk weights are not only an important transmission channel of shocks from the real economy to the banking sector, but can also be the cause of shocks to the banking sector. The shock $e^{\varepsilon_t^{RW_i}}$ affects the steady-state level of risk weights and is used to assess the impact of changes to sectoral capital requirements. In addition, the impact of different regulations on the risk weight can also be analysed by assuming a different formulation of the risk weights formula.

3.4 Shock to the interest rate mark-ups of the loan book financing branches

Another source of financial shocks to the real economy originates in the loan book financing branches where banks have some degree of market power, as loans from loan book financing branches are imperfect substitutes. Loan book financing branches face in each period a constant probability of being able to adjust their nominal interest rate on loans. In each sector $i \epsilon \{E, HH\}$ the loan financing branch j chooses an optimal lending rate $\hat{R}_{i,t}(j)$ to maximise its intertemporal profit

$$E_t \left[\sum_{k=0}^{\infty} (\gamma \xi_i^R)^k \frac{\Lambda_{t+k}}{\Lambda_t} \left((1 + \varepsilon_{i,t}^R) \hat{R}_{i,t}(j) B_{i,t+k}(j) - R_{i,t}^{wb}(j) B_{i,t+k}(j) \right) \right] \tag{7}$$

where $B_{i,t+k}(j)$ is defined as $B_{i,t+k}(j) = \frac{\hat{R}_{i,t}(j)}{R_{i,t}}^{-\frac{\mu_i^R}{\mu_i^R - 1}} \frac{R_{i,t}}{R_{i,t+k}}^{-\frac{\mu_i^R}{\mu_i^R - 1}} B_{i,t+k}$ and $\varepsilon_{i,t}^R$ denotes a mark-up shock to the wholesale branches lending rate.

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86 As explained in Section 4.2, the model allows an exogenous increase in capital. Therefore, it is still possible to simulate a contemporaneous increase of capital and deleveraging.

As loans to entrepreneurs and households are CES aggregates of differentiated loans across loan book financing branches, the average lending rates are defined as

$$R_{i,t} = \left[\int_0^1 R_{i,t}(j)^{\frac{1}{1-\mu_i^R}} \, dj \right]^{1-\mu_i^R} \quad , i \in \{E, HH\} \tag{8}$$

A higher credit risk premium charged by the loan book financing branches on loans to households and/or entrepreneurs increases the loan rate and has an immediate negative impact on GDP growth as it reduces the demand for loan financing. In line with equations (1)-(6), the leverage of the wholesale branches decreases, as this reduces the risk-weighted assets. At the same time, a reduction in lending would have an impact on profits and retained earnings too. The transition to the target capital ratio is then a combined change in both the bank capital and the risk weighted assets. The central bank can shorten the transition to the new equilibrium by lowering its policy rate.

4 Application: impact assessment of macroprudential policies

This section illustrates how the shocks presented in the previous sections are used in practice for the impact assessment of macroprudential policies on the real economy. Despite the establishment of macroprudential authorities in various jurisdictions in advanced economies, there is still very limited experience with the implementation and effectiveness of macroprudential policies, how they should interact with monetary policy, and what the synergies and potential trade-offs are.[87] Moreover, the literature that attempts to quantify the impact of macroprudential policies is still very limited.[88] Within the models presented in this chapter, the macroeconomic propagation within the monetary union of selected macro-prudential instruments can be analysed, namely:

1. *system-wide bank capital requirements*, which increase the resilience of the banking system as a whole by ensuring adequate buffers to cope with losses;
2. *sectoral capital requirements*, which, in contrast, only make lending to certain classes of borrowers more costly and hence prompt banks to reduce their activity in that specific segment; and
3. *loan-to-value ratio restrictions* pertaining to the banks' assets side, directly affecting the borrowing constraints of their customers, and hence make the banking system less vulnerable to borrower defaults.

[87] The lack of a clear consensus should also be seen in the light of still-limited practical experience with macroprudential policies in the advanced economies; see also the special feature in ECB (2014) and the references quoted therein. See also Bruno et al. (2015).

[88] See Martynova (2015) for a survey on the effects of bank capital requirements on economic growth.

4.1 Macroprudential stress testing: impact assessment of second-round effects on the macroeconomy

DSGE models are used to study the second-round effects of an adverse macro-financial scenario on the macroeconomy, such as, for example, the scenario underlying the EBA stress-test. One of the main assumptions of the EBA stress test exercise is that banks do not raise capital or deleverage in response to the macroeconomic scenario, to the extent that according to the methodology the downward activity shock has no impact on, for example, the size of their loan book. The EBA stress test exercise is namely a partial equilibrium exercise, assuming that banks do not react to the macroeconomic scenario. This assumption is discarded when assessing the second-round effects of the stress test exercise.

In this case, it is assumed that on top of adjusting credit supply to credit demand under the adverse scenario, banks also respond through an upfront adjustment to their capital ratio to conform to some target capital ratio. This, in turn, would amplify or dampen the severity of the macroeconomic scenario and hence the effect on the loan supply. The additional effect on the loan supply due to the banks' endogenous reaction to the adverse scenario is what is considered a second-round effect. The magnitude of the second-round effects would depend on the adjustment strategy adopted by the banks, and on the target capital ratio.

The target capital ratio could be determined by the supervisor, as in the 2011 and 2014 EU-wide stress testing exercises, or it could be an internal bank target. In the latter case, such targets may be set with the objective of reassuring bank investors – creditors and shareholders – about the soundness of the bank, thus reflecting market discipline and benchmarking to stronger banks. The choice of the capital target is central to the magnitude of the economic impact; the higher the target, the more severe the potential consequences of the banks' adjustment for the economy. To quantify the distance of the actual CET1 ratio from the target capital ratio, it is assumed that adjustment of the capital ratio occurs only for banks with a CET1 ratio below these target capital ratios in the bottom-up stress testing exercise under the adverse scenario. As an illustration, two assumptions for capital ratio targets are reviewed, i.e. 6% and 8% CET1 for the macroprudential extension of the stress test, which are higher than the past supervisory targets used in the EU-wide stress testing exercises.

Assuming that banks would have targeted CET1 ratios of 6% and 8% CET1 ratio at the end of 2018, the next step is to compute the country aggregate capital shortfalls of banks in the adverse scenario using the bottom-up (i.e. banks' own) stress test results. The DSGE model is then employed to quantify the impact that the aggregate capital shortfalls would have on the macroeconomy. Then the scenario is updated to include this amplification effect. Chart 10.3 graphically illustrates where the DSGE model is used in the macroprudential extension of the stress test.

Chart 10.3

Use of the DSGE model in the macroprudential extension of the stress test

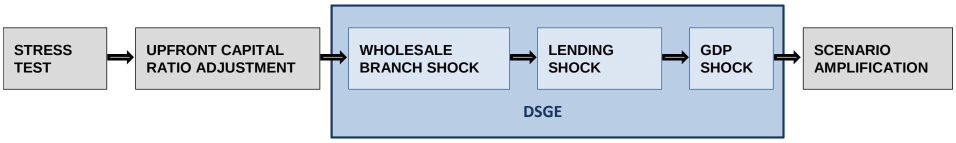


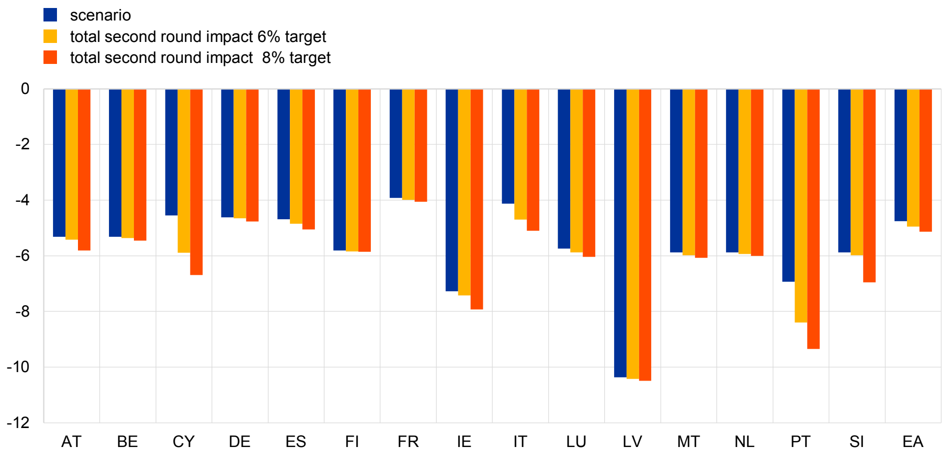
Chart 10.4, reports an example of a simulated scenario and the corresponding second-round effects on real GDP calculated using the DSGE model. The chart illustrate the total deviation of real GDP from the baseline at the end of the scenario horizon and total GDP shocks including second-round effects as estimated by the DSGE model. The overall impact on GDP is obtained by adding the shock to GDP derived from the capital shortfalls to the initial scenario shocks. For this simulation it is assumed that the banks' capital ratio drops below the steady state capital ratio target (see Section 3.2). Second-round effects are negligible for the macroeconomy for most of the countries, as capital shortfalls are concentrated in few jurisdictions. For Portugal, Slovenia, Cyprus and Ireland, the second-round impact on GDP can reach 1%.

Chart 10.4

Second-round effects of the stress test scenario on GDP

GDP shock after 3 years in a simulated scenario and total second-round effects assuming that banks have either a 6% or 8% target for CET1 ratio

(percentage point deviation from baseline)



4.2 System-wide capital requirements

An increase of system-wide capital requirements can be simulated in the model using three different shocks that are described in Section 3:

- **Assuming a lending spread shock**: in this case, it is assumed that banks would increase the mark-up in order to achieve the necessary deleveraging to converge to a new capital ratio. This case is also called “full deleveraging”, because it affects directly the supply of credit.

- **Assuming an exogenous shock to capital**: in this case, it is assumed that banks’ capital exogenously drops such that the capital ratio would fall below its long-run steady-state value.
- **Assuming a shock to the capital target**: in this case, it is assumed that the steady-state/target capital ratio of banks increases.

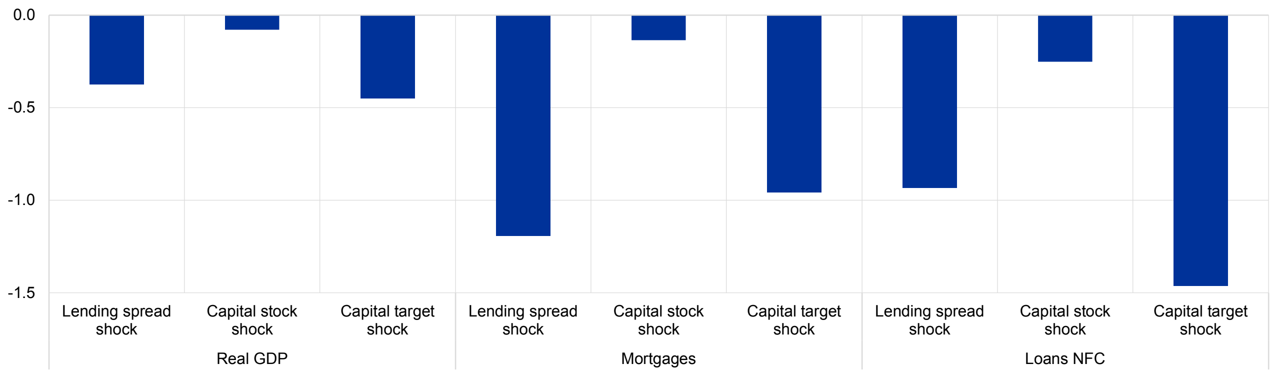
Given that banks are in monopolistic competition and cannot decide to raise equities, all shocks are transmitted to the private sectors via an increase in lending spreads, as described in the previous section. Chart 10.5 compares the deviation with respect to the baseline of real GDP, mortgage lending and credit to non-financial corporations for the euro area assuming that a change in the capital ratio is caused either by a change in lending spreads (full deleveraging), an exogenous shock to the capital stock, or a shock to the banks’ capital ratio target. Chart 10.5 compares only the effects after one year assuming that at the end of the first year the capital ratio changes overall by one percentage point. As seen in Chart 10.5, the implementation of a system-wide capital requirement via an exogenous shock to the capital stock has a significantly lower impact on the real economy. However, the model does not consider the costs of raising equity and, in this sense, underestimates the negative impact on the real economy.

Chart 10.5

Impact on the real economy of system-wide capital requirements

Impact on real GDP, mortgage lending and credit to non-financial corporations of a shock to the lending spread, the capital ratio target and the capital stock

(percentage deviation from the baseline)



4.3 Sectoral capital requirements

A change in sectoral capital requirements is simulated via an exogenous shock to the risk weight of either credit to households or credit to non-financial corporations. Sectoral capital requirements generally have a less adverse impact on real economic variables as they are more targeted measures and do not necessarily imply a deleveraging but rather a reallocation of banks’ lending activity. Charts 10.6 and 10.7

compare the average impact on real GDP during the first year of a shock to the system-wide capital requirement and of sectoral capital requirements for mortgage lending (Chart 10.6) and non-financial corporation lending (Chart 10.7). The impulse responses are standardised such that system-wide capital requirements and sectoral capital requirements are comparable, which lead on average in the first year to a reduction of credit to households (Chart 10.6) and to non-financial corporations (Chart 10.7) of 1 percentage point. As seen in Chart 10.6, sectoral capital requirements on mortgages have a positive impact on the real economy as this leads to a reallocation of credit to the non-financial corporations, boosting production. Conversely, tighter sectoral capital requirements on credit to non-financial credit corporations would have very negative adverse effects on the real economy (see Chart 10.7).

Chart 10.6

Impact on real GDP of system-wide and sectoral capital requirements

System-wide capital requirements and sectoral capital requirements on mortgage lending

(percentage deviation from the baseline)

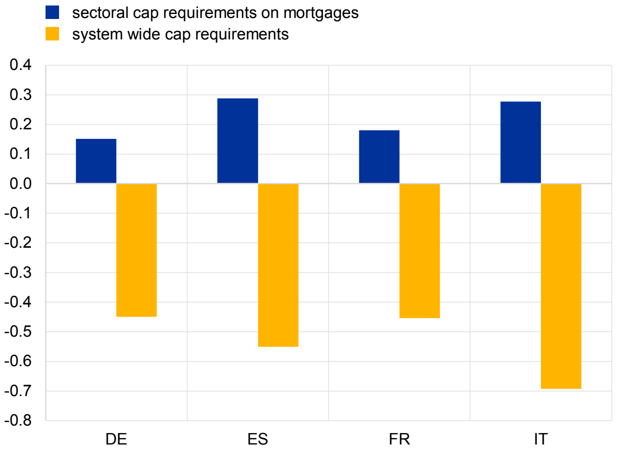
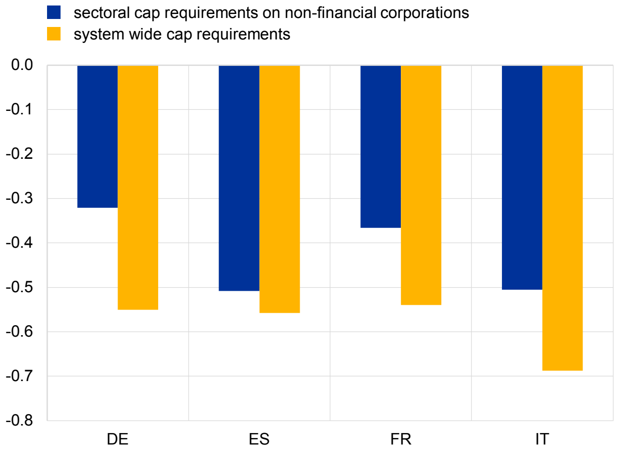


Chart 10.7

Impact on real GDP of system-wide and sectoral capital requirements

System-wide capital requirements and sectoral capital requirements on credit to non-financial corporations

(percentage deviation from the baseline)



4.4 Loan-to-value ratio caps

This section illustrates how DSGE models can be used to compare different macroprudential policies designed to prevent excessive housing price increases. In particular, the risk of a region-specific gradual rise in house prices of 10% over a two-year horizon, fuelled by positive housing demand factors and loose credit supply conditions relating to loans for house purchases, is considered. Buoyant construction activity, together with the relaxation of financial constraints for the households sector, support growth momentum and consumer spending in the booming region. The baseline simulation assumes that monetary policy is unchanged for two years.

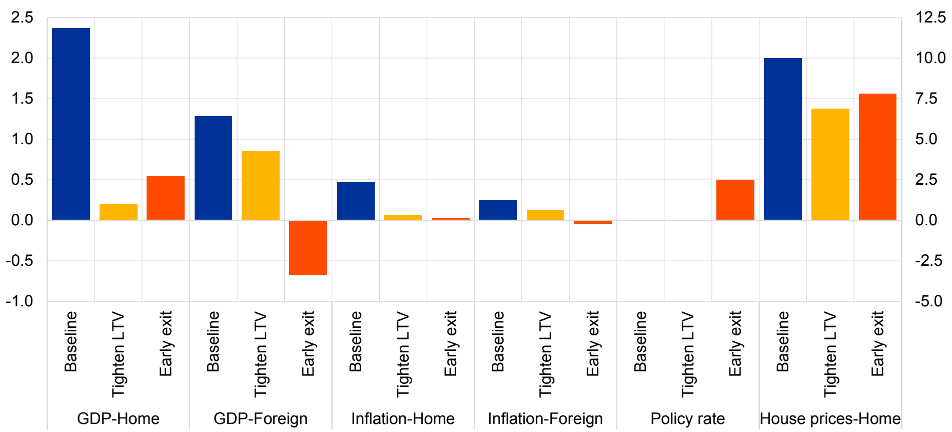
Against this background, two scenarios are considered. In the first scenario, a countercyclical macroprudential intervention in the booming region is introduced through a cap on loan-to-value ratios while monetary policy is kept constant. In the second scenario, the early exit from the exceptionally loose monetary conditions is proxied by letting the policy rate rise three quarters earlier than in the baseline scenario to ensure that average inflation rate is equal to average inflation rate under the baseline. The respective simulations are presented in Chart 10.8. The result is that the macroprudential measures contain the asset price increase in the booming region and shield the rest of the euro area at the same time. By comparison, the early tightening of monetary policy to mitigate house price growth in the domestic economy delivers significantly more cross-country heterogeneity and negative cross-border spillovers.

Chart 10.8

Targeted macroprudential interventions to curtail financial imbalances in the housing market

Prevention of house price bubbles: loan-to-value ratio measures versus monetary policy

Cumulative responses after two years: real GDP (percentage deviation from baseline, left-hand scale), inflation (percentage point deviation from baseline, left-hand scale), policy rate (percentage point deviation from the baseline, left-hand scale); house prices (percentage deviation from baseline, right-hand scale);



4.5 Changes in the formulation of risk weights

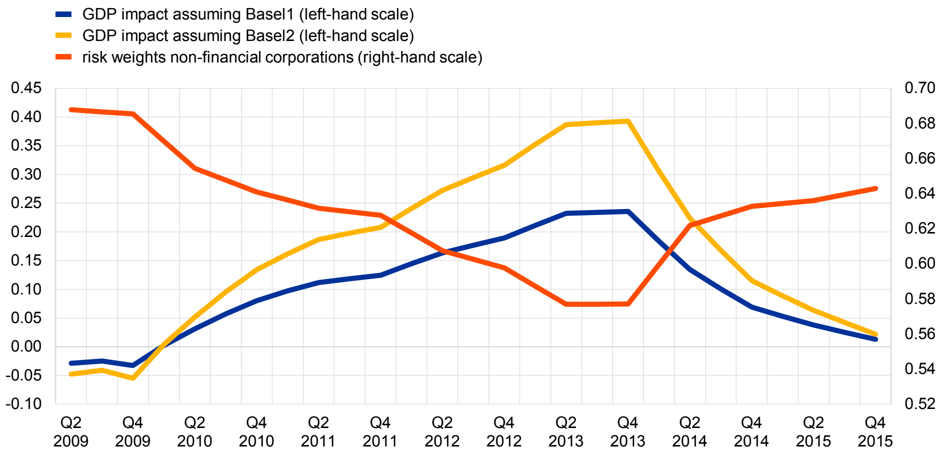
This section presents a counterfactual study to assess the impact of applying the Basel I instead of the Basel II risk weights formulation. The simulations are based on the aggregated series of the euro area risk weights on lending to non-financial corporations. Assuming that the Basel I formulation of risk weights is in place would imply that the risk weight of banks would not change over time. Following the Basel II formulation, however, the risk weights would increase during the crisis periods. Chart 10.9 shows how the model can replicate the more pro-cyclical effects of the risk weights formulation under Basel II relative to Basel I. The overall effect on the capital ratio would then be more negative (positive) during crisis (upturns) using the Basel II formula. Similarly, the lending behaviour and, hence, the overall effect on GDP would then be more pro-cyclical using the Basel II risk weights formulation.

Chart 10.9

Use of the DSGE model for the impact assessment of different formulations of the risk weights

Impact on real GDP of shocks to the probability of default of non-financial corporations assuming that risk weights follow the Basel I and Basel II formulation

(percentage deviation from the baseline, left-hand scale; basis points, right-hand scale)



5 Conclusions

DSGE models with financial frictions that are generally used to estimate the effects of changes in the monetary policy stance are also suitable instruments to analyse the impact of macroprudential policies, particularly in the context of limited data availability and multiple policy choices.

Currently, the most relevant applications of these models are (i) the macroprudential extension of the supervisory stress test, and (ii) the impact assessment of macroprudential policies both for the euro area as a whole as well as at the level of individual countries. In the first case, DSGE models are used to assess the second-round effects on GDP and real economic variables of an upfront adjustment of banks’ capital ratios. In the second case, DSGE models are used to evaluate the costs and benefits of changes to (system-wide or sectoral) capital requirements, changes to the formulation of risk weights, or changes in loan-to-value ratio caps.

The use of DSGE models is an important first step for analysing macro-financial linkages which, however, needs to be further complemented by micro-level analysis at the level of individual banks.

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Chapter 11 Assessing second-round effects using a Mixed-Cross-Section GVAR model

By Marco Gross and Dawid Żochowski

This chapter presents a large-scale semi-structural model that can be used to assess the relationship between bank capital, lending and the macroeconomy. It enters the toolkit employed for macroprudential analyses next to micro data-based risk-specific models (as presented in Chapters 4 to 8) and aggregate general equilibrium models (Chapter 10). The tool at hand, a Mixed-Cross-Section Global Vector Autoregressive (MCS-GVAR) model, can be used to assess the macroeconomic effects of bank capital changes in general and asset-side deleveraging scenarios in particular. The model can provide bank-level responses and cross-country spillover estimates.

The model allows various scenarios to be simulated for managerial actions at the bank or country level – from full contractionary deleveraging, when banks shed assets in response to stress, to a mixed scenario, where banks partially shrink and at the same time accumulate or raise capital as a buffer against losses resulting from stress. In the model, the initial capital shock translates into an impact on the domestic economy and propagates to other EU economies through the trade channel and through the cross-border lending channel. The model can be used to establish ranges of impact estimates for GDP following the initial capital shortfall resulting from the stress, which may also depend on the deleveraging strategies adopted by individual banks.

1 Introduction

This chapter presents a model which can be used to assess how bank leverage, via its impact on credit supply, influences business cycle dynamics both at the domestic level and across borders in the EU. The questions that can be addressed in this framework are, for example, whether it makes a difference for macroeconomic outcomes if deleveraging is accomplished by shedding assets or by raising capital. One can also assess the significance of any cross-bank and cross-border effects of bank deleveraging shocks in terms of loan supply and economic activity. The model has been estimated using both individual bank balance sheet data and banking sector aggregates. Both model specifications offer valuable insights into the endogenous macro-financial linkages across EU countries and banking systems.

The Mixed-Cross-Section feature of the GVAR model deserves special emphasis. It allows different cross-section types to be combined, for instance countries with banks/banking systems, central banks, etc. Individual bank balance sheet data in the bank cross-section are combined with macroeconomic variables in the country cross-section and policy rates in the central bank cross-section (see Gross, Kok and Żochowski, 2016, and Gross, Henry, and Semmler, 2017).

Section 2 presents the structure of the model. Section 3 shows some illustrative simulation results from the model. Section 4 concludes.

2 Model structure

The MCS-GVAR model comprises three cross-sections: a cross-section of $i = 1, \dots, N = 28$ EU countries, a cross-section of financial institutions $j = 1, \dots, M =$ and a central bank cross-section $l = 1, \dots, B = 11$ of the ECB and 10 non-EA EU national central banks. The endogenous variables belonging to the three cross-sections are collected in the vectors x_{it}, y_{jt} and z_{lt}, respectively. For a given cross-section item at a point in time t, the three vectors are of size $k_i^x \times 1, k_j^y \times 1$ and k_l^z. The model has the following form:

$$x_{it} = a_i + \sum\nolimits_{p_1=1}^{P_1} \Phi_{ip_1} x_{i,t-p_1} + \sum\nolimits_{p_2=1}^{P_2} \Lambda_{i,0,p_2} x_{i,t-p_2}^{*,C-C} + \sum\nolimits_{p_3=1}^{P_3} \Lambda_{i,1,p_3} y_{i,t-p_3}^{*,C-B} + \sum\nolimits_{p_4=1}^{P_4} \Lambda_{i,2,p_4} z_{i,t-p_4}^{*,C-CB} + \epsilon_{it}$$

$$y_{jt} = b_j + \sum\nolimits_{q_1=1}^{Q_1} \Pi_{jq_1} y_{j,t-q_1} + \sum\nolimits_{q_2=1}^{Q_2} \Xi_{j,0,q_2} x_{j,t-q_2}^{*,B-C} + \sum\nolimits_{q_3=1}^{Q_3} \Xi_{j,1,q_3} y_{j,t-q_3}^{*,B-B} + \sum\nolimits_{q_4=1}^{Q_4} \Xi_{j,2,q_4} z_{j,t-q_4}^{*,B-CB} + \omega_{jt}$$

$$z_{lt} = c_l + \sum\nolimits_{r_1=1}^{R_1} \Gamma_{lr_1} z_{l,t-r_1} + \sum\nolimits_{r_2=1}^{R_2} \Psi_{l,0,r_2} x_{l,t-r_2}^{*,CB-C} + \sum\nolimits_{r_3=1}^{R_3} \Psi_{l,1,r_3} y_{l,t-r_3}^{*,CB-B} + \sum\nolimits_{r_4=1}^{R_4} \Psi_{l,2,r_4} z_{l,t-r_4}^{*,CB-CB} + \tau_{lt}$$

The intercept terms a_i, b_i and c_i are of size $k_i^x \times 1, k_j^y \times 1$ and k_l^z, respectively. Global exogenous variables can be added to the model but are not, however, included here. The three equation blocks contain a set of autoregressive terms – $(\Phi_{i1}, \dots, \Phi_{iP_1}), (\Pi_{j1}, \dots, \Pi_{jQ_1})$ and $(\Gamma_{l1}, \dots, \Gamma_{lR_1})$. The within and across-cross-section dependence is then introduced via the star variable vectors. The cross-section-specific shock vectors – $\epsilon_{it}, \omega_{jt}$ and τ_{lt}– are of size $k_i^x \times 1, k_j^y \times 1$ and k_l^z, respectively. They have zero mean, are serially uncorrelated and have covariance matrices $\sum_{ii}^x \sum_{jj}^y \sum_{ll}^z$. A global covariance matrix $\sum$ captures the covariance structure of the combined set of residuals from all three equation blocks. In this Mixed-Cross-Section variant of the GVAR three cross-sections, up to nine sets of weights are necessary to set up the model.

The country cross-section of the model includes nominal GDP, a GDP deflator, nominal residential property prices and long-term interest rates. The banking sector-related variables include: nominal credit[89], loan interest rates, deposit rates, a

[89] The loan volume variable reflects either consolidated total loans at the bank level from public data sources or aggregated banking system loan volumes.

leverage multiple defined as total assets over total equity, and the probability of default of the bank(s). The central bank cross-section includes one variable, namely the short-term policy rate from the respective currency areas.

The model is estimated using a number of exclusion restrictions for each equation that are justified by theory. While the imposition of structural constraints is new in a GVAR model context it is a familiar feature characterising large-scale equation systems such as bank stress testing frameworks or the large-scale macro models used to produce macroeconomic projections.

Table 11.1 provides an overview of the structure of the model. Channels may operate *globally* (2), via weights usually employed in the GVAR context or *locally* (1), meaning that a direct relationship between variables can only exist within a country or within a bank/banking system. The third option is for a channel to be *closed* (0), which means that the corresponding coefficients in the model are set to zero.

Table 11.1
MCS-GVAR model structure

Cross-section type	Model variable		GDPN	GDPD	RPP	LTN	L	LEV	I	D	PD	STN
Countries	Nominal GDP	GDPN	2	2	2	2	2	0	2	2	0	2
	GDP deflator	GDPD	2	2	2	2	2	0	0	0	0	2
	Residential property prices	RPP	2	2	2	2	2	0	2	0	0	2
	Long-term interest rate	LTN	2	2	2	2	0	0	0	0	0	2
Banks	Nominal loan volumes	L	2	0	2	0	2	1	1	0	0	0
	Leverage (TA/E)	LEV	0	0	0	0	1	0	0	0	0	0
	Interest income/assets (or loan interest rate)	I	2	0	2	2	0	1	2	1	0	2
	Interest expense/liabilities (or deposit rate)	D	2	0	0	2	0	1	1	2	0	2
	Probability of default	PD	0	0	0	0	1	1	0	0	0	0
Central banks	Short-term policy rate	STN	2	2	0	0	0	0	0	0	0	0

Notes: The table shows the channels through which shocks are allowed to propagate, which are imposed via sign restrictions. Channels operate *globally* (2), via weights usually employed in the GVAR context, *locally* (1), i.e. within a given cross-section, or are *closed* (0).

Aggregate economic activity, measured by nominal GDP, can be driven by all country cross-section variables, credit provided by banks, bank lending rates, the cost of funding of banks as well as short-term interest rates.[90] The cross-country economic activity link is justified by the standard trade channel: a fall in aggregate demand in one country leads to lower imports from other countries, thereby reducing economic activity abroad. Similarly, the link via residential property prices and long-term interest rates is justified by wealth and discount rate effects respectively. The link through loan volumes reflects the role the financial sector, specifically banks, plays in the economy by providing funds for investment and consumption which, in turn, directly affects economic activity.

[90] Nominal GDP is included in the model instead of real GDP as it more naturally relates to nominal credit. In terms of empirical (in-sample) predictive performance, the nominal measure is indeed more strongly related to the remainder of the model variables. Real GDP responses to the scenarios that are going to be simulated with the model can always be derived as an "off-model" variable as the difference between nominal GDP growth and inflation.

The bank lending rate variable reflects the effective interest rates that households and firms pay for bank financing, while the funding cost measure is related to the effective interest rates that economic agents receive for depositing their money with the banks. The link with the economic activity variable is justified via at least two channels. First, higher interest rates, ceteris paribus, mean that fewer profitable projects can be financed through the creation of credit, and imply lower economic activity. In addition, existing projects may be discontinued, since financing costs may start exceeding the average rate of return on a project. In an intertemporal setup, higher interest rates encourage households to postpone their consumption and save more today, which also reduces current economic activity and affects the supply of deposits. While the literature suggests that bank leverage or bank PDs could impact economic activity via loan supply, if anything this could only work by assumption through indirect third channels to the extent that, for instance, they influence loan supply.

The channel for aggregate nominal activity, the GDP deflator, is also open to all variables in the country cross-section. The channels and the argumentation are the same as for aggregate economic activity above. Moreover, loan growth at the bank level may influence aggregate prices. It is assumed that excessive loan growth, if stimulated at a time of strong expansion when firms are operating close to their capacity constraints, may exert direct upward pressure on prices, as firms can no longer satisfy demand by increasing production.

House prices can be driven by all macro variables in the country cross-section. The relationship between house prices and macroeconomic variables is documented by both economic theory and the vast empirical literature. Empirical studies provide evidence that real disposable income, real interest rates, loan growth and other supply side factors all affect house price dynamics. Moreover, residential property prices are allowed to be affected by loan growth and lending rates from the bank cross-section in order to reflect the empirical evidence that loan growth is associated with price increases in the residential property market.[91] Long-term interest rates are proxied by 10-year benchmark government bond yields. It is assumed that they are not driven through any direct channel by bank variables.

Nominal credit at the bank level can be a function of nominal GDP, house prices, bank lending rates and bank leverage. Moreover, it can be a function of the weighted aggregate credit provision from the other banks in the system. For GDP, a cross-country channel is allowed to be open, to reflect the fact that banks can have cross-border exposures and are affected by changes in demand from countries to whose residents they provide credit. Similarly, the house price link is also open in a cross-country dimension as boosting the value of housing collateral impacts bank lending via two wealth effect channels. First, since houses are used as collateral, higher house prices strengthen households' borrowing capacity. Second, in life-cycle models a higher value of households' wealth may increase lifetime consumption and impact today's demand for credit, smoothing consumption over the life cycle. For

[91] For all links to the theoretical and empirical papers from the literature referred to in this section, see the references in Gross, Kok and Żochowski (2016) and Gross, Henry, and Semmler (2017).

bank leverage, it is assumed that only the banks' corresponding own measures may relate to their balance sheet structure. Finally, the bank lending rate is allowed to impact loan volumes at the bank level only, to the extent that a given bank can steer its own credit demand by adjusting its credit margins.

The leverage variable at the bank level is allowed to be a function of credit (only the bank's own corresponding measure) for the obvious reason that leverage is a mechanical function of its own assets.

Bank lending rates can be affected by GDP, house prices, long-term interest rates, bank leverage, bank lending rates, the cost of funding, and short-term policy rates. For GDP the global channel is open, as the asset returns of banks that engage in cross-border business may be driven by macro conditions abroad. The house price channel is also allowed in a cross-country dimension as a change in property values may directly affect loan interest rates to reflect changing collateral values and, therefore, risk. This is because residential property prices affect the value of a bank's capital via the quality/value of mortgages secured by houses and, therefore, the price of credit. Long-term interest rates in the jurisdiction in which a bank operates will impact the interest rates on loans originated in those countries via their effect on borrowers' net worth and thus creditworthiness, and via their effect on bank funding costs (see also below). For leverage, only the banks' own corresponding measures can impact their loan rates. In turn, the cost of funding is allowed to impact bank lending rates to reflect the fact that banks, to a large extent, pass higher funding costs through to their borrowers. For bank asset returns themselves, a cross-bank channel is open as, due to competitive pressures, one bank may adjust its asset prices in response to another bank's asset price changes. The literature suggests that competition between banks results in a faster bank interest rate pass-through.

The cost of banks' debt (deposit rates in the banking system version) is allowed to be a function of GDP, long and short-term interest rates, bank leverage, and the cost of funding of other banks.[92] For internationally active banks, global growth and implied market volatility, as well as short-term interest rates and the slope of the yield curve, determine bank funding costs. Furthermore, it is allowed that the cost of funding may be driven by the cost of funding of other banks. This channel is a direct price spillover channel which, particularly during times of economic turmoil and recession, is important since banks are, at times, known to engage in "deposit wars", where the cost of funding is, in a controlled manner, adjusted upwards to attract depositors. This link is justified by the market power hypothesis, whereby banks can set deposit rates according to the extent of competition in the deposit market. In particular, for the deposit market, competition raises the optimal risk choice of the bank by raising the cost of bank liabilities. In general, the cost of funding is expected to be correlated, on average, across banks over the business cycle. Finally, it is allowed that the cost of funding may be driven by leverage.

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92 For GDP it may be argued that banks are more price setters of deposits and are therefore fairly inelastic to changes in aggregate demand. While this argument has some merit, this channel is nonetheless allowed to be present since the cost of funding, in the way it is measured here, captures not only the cost of deposits, but also the cost of wholesale funding instruments (for which banks tend to be more price takers than setters).

It is assumed that the probability of default of a bank is a synthetic measure of the risk for the bank balance sheet which, given the current set of model variables, is best represented by loan growth and leverage. Loan growth, which in this context may be seen as a proxy for asset volatility, and leverage are the two main determinants of the probability of default, following a standard Merton model rationale.

The short-term policy rate for the various currency areas are included in both model variants, with a Taylor-rule rationale determining the shape of the short-term rate equation, i.e. for a direct link established to GDP and the GDP deflator.

In terms of model structure, one autoregressive lag and the contemporaneous and first lag of all weighted cross-border and cross-bank variable vectors are allowed to appear in the model. The model is estimated on the basis of data covering the period 1999Q1-2015Q4 (68 observations). It is a partially unbalanced panel as the time series for a few institutions and countries in the sample are either shorter or not available. The individual equations are estimated by means of an iteratively reweighted least squares method.[93] The global model is stable, with its maximum modulus of the eigenvalues of the companion coefficient matrix being less than 0.7. For an outline of how the global model is "solved", see Gross, Kok and Żochowski (2016). The solution step is necessary, as in all standard GVAR applications, since the initial model structure involves time contemporaneous relationships which, as such, prevent its use in scenario simulations and forecasting.

3 Simulating deleveraging scenarios

Two types of shock to bank leverage are considered. The initial shock is defined as a negative percentage point shock to leverage (ΔLEV). The following description of the shock setting applies to both the individual bank and the banking system version of the model.

Full deleveraging: this represents a negative credit supply shock. It is assumed that the capital ratio shock translates fully into asset-side deleveraging, under an assumption of constant equity capital. It is assumed that outstanding debt shrinks in line with assets to reflect the destruction of credit/money that the repayment and non-renewal of credit implies.

Mixture of capital raising and asset deleveraging: the capital ratio shock is not translated into credit supply shocks but is taken directly as a starting point for the shock simulation, without any constraints on the adjustments of banks' balance sheets. This scenario is referred to in what follows as an "empirical scenario".

The shock, in the case of full deleveraging, which may be thought of as a *polar case*, is implemented by means of a sign restriction methodology. The assumed drop in

[93] This method is more robust in respect of outliers than ordinary least squares and helps stabilise the dynamics of the global model. A Cauchy weighting function is used for the weighting scheme. This choice of weighting function has no material impact on the results from the model.

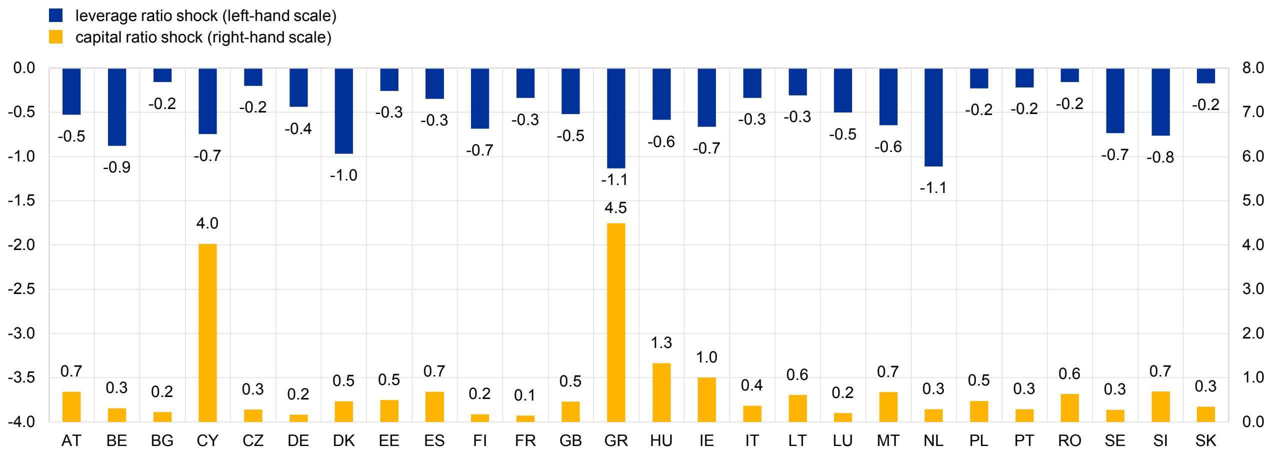
credit growth is combined with a positive sign constraint on loan interest rates in the same banking system. The aim of the sign constraint is to identify the impulse as a negative credit supply shock. The sign constraints are only imposed in the first period.[94]

Chart 11.1 shows the magnitude of shocks – expressed in terms of both leverage multiple and capital ratio shocks – for the banking system aggregates. They reflect a 1-standard deviation of the residuals from the two versions of the MCS-GVAR model.

Chart 11.1

Leverage and capital ratio shocks

(leverage multiple change; capital ratio change, percentage points)



Notes: The leverage ratio is defined as total assets over equity, whereas the capital ratio is defined as equity over total assets. The shock sizes are implied by the historical model residuals (1 standard deviation).

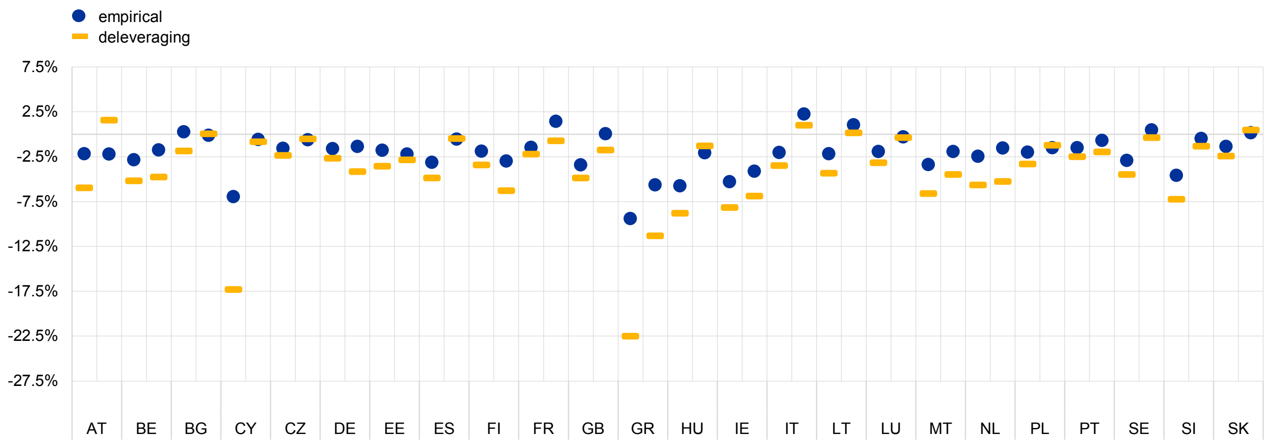
Chart 11.2 shows the corresponding loan supply shocks under the full asset-side deleveraging scenario, along with the endogenous responses of credit under the empirical capital ratio shock scenario. The magnitude of the shocks under the deleveraging scenario is a function of two features of the banks (banking systems): the size of the shocks to the capital ratios (model residual-based) and the initial capital ratio of a bank (banking system) at the start of the simulation horizon. For example, for two banks with an (assumed) equal residual standard deviation for their leverage variable from the model, the bank with a higher initial leverage multiple (lower capital ratio) will be assigned a more pronounced fall in asset growth under the deleveraging simulation, reflecting its higher balance sheet leverage compared with the other bank.

[94] This identification scheme circumvents the fact that while banks, having raised fresh equity, should be in a position to supply more credit for a given loan demand, hence pushing lending rates down, the new equity raised will also imply a dilution of existing shareholders and will reduce the return on equity (ROE). This might be expected to induce banks to increase lending margins in order to reinstate their desired ROE target. Indeed, by only imposing the sign restriction in the first period, our simulations allow for such rent-seeking behaviour in subsequent periods.

Chart 11.2

Gross loan growth shocks under asset-side deleveraging and loan growth responses under an empirical capital ratio shock scenario

(natural log percentage points)



Notes: The responses are expressed as long-run log percentage point deviations from baseline growth. Under the deleveraging scenario, the loan growth effect is a shock. Both scenario types start from the same capital ratio shock per banking system. The left-hand column for each country reflects the domestic effects; the right-hand column reflects the weighted foreign effects.

The sizes of the shocks under the controlled deleveraging scenario are spread over a cumulative three-year horizon. For the asset-side deleveraging simulations this scaling is based on the implied loan supply shocks, while under the empirical capital ratio shock scenario the scaling is based directly on the underlying capital ratio shocks.[95]

Shock correlations across countries or banking systems are assumed to be zero in the first period of the simulation. The pair-wise cross-section residual correlation is small (0.05 on average) and the simulation results are robust, allowing the cross-country correlations to be non-zero. A contemporaneous reaction to shocks in the country or banking system in which the shock originates is allowed to be non-zero, for both macro and bank/banking system variables.

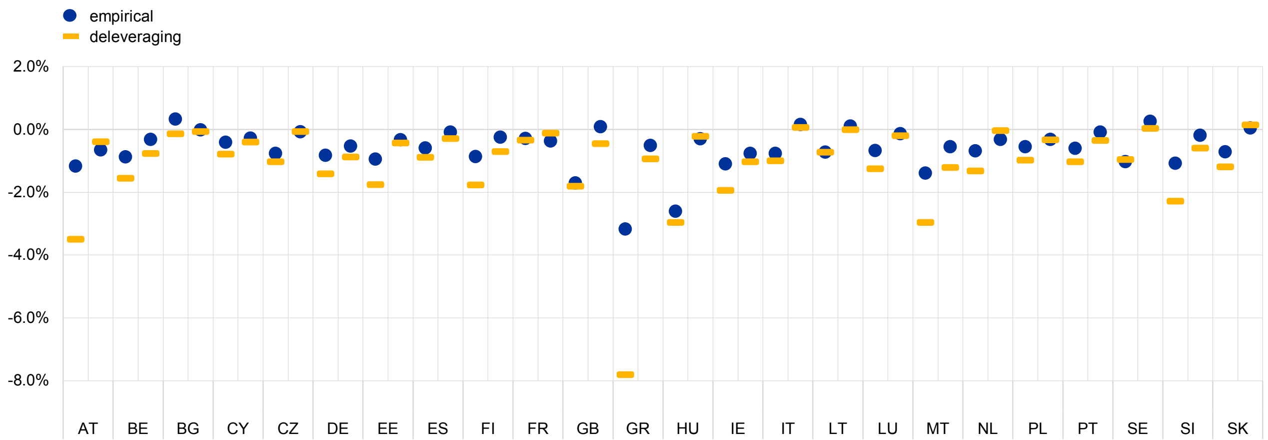
Chart 11.3 shows the three-year cumulative scenario responses for real GDP from the country cross-section. The real GDP responses are computed by subtracting the GDP deflator responses from nominal GDP responses.

95 While the overall capital ratio is under control, as it is included in the model and assigned a specific post-shock target for all simulation types, there is only partial control over how assets adjust, as only credit is included in the model, and no assets other than credit. The fact that this non-credit residual is not included in the model means that the amount of debt required to actually make the balance sheet balance is not explicitly quantifiable or controllable (as is the case for the amount of total assets).

Chart 11.3

Responses of real GDP to deleveraging shock scenarios

(natural log percentage points)



Notes: The responses are expressed as long-run log percentage point deviations from baseline growth. Both scenario types start from the same capital ratio shock per banking system. The left-hand column for each country reflects the domestic effects; the right-hand column reflects the weighted foreign effects.

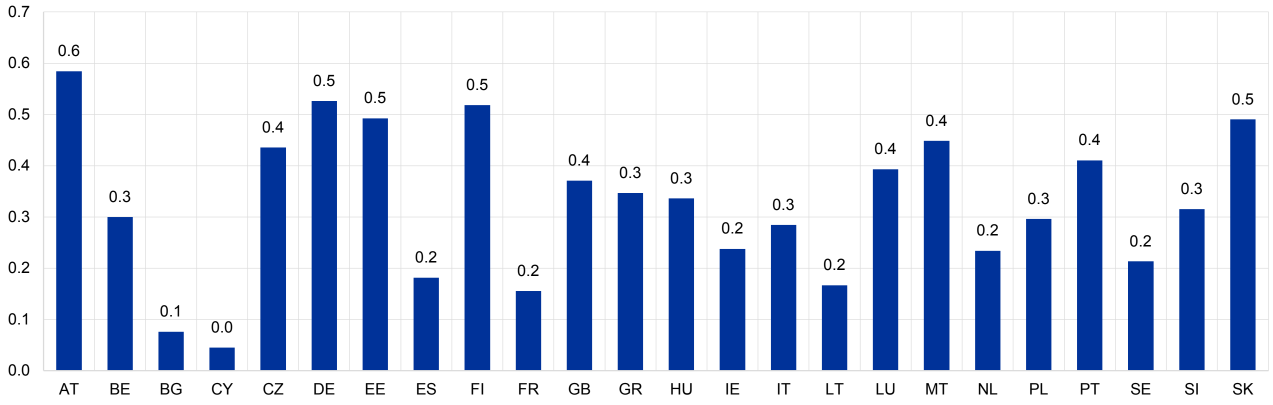
Both the domestic responses and the weighted cross-border responses are displayed in the same charts (for each country or bank/banking system in two side-by-side columns). The cross-border dimension in the second column is compressed by computing weighted average responses, the weights being the banks' or banking systems' loan exposure profiles as of 2015. For macroeconomic responses, the loan exposure-based weights are used, the argument being that for banks, trade exposures are not directly relevant, whereas the cross-border lending activity of banks constitutes a more appropriate direct shock propagation channel.[96] With regard to the real GDP responses, two additional summary measures are provided. Chart 11.4 shows the real GDP to nominal loan growth shock long-run multipliers, while Chart 11.5 shows the ratio of weighted foreign GDP responses to domestic GDP responses.

[96] When using trade weights instead of exposure weights for the purpose of an ex post aggregation of, for example, the GDP responses, the weighted responses tend to be systematically smaller.

Chart 11.4

Real GDP to nominal loan growth multipliers

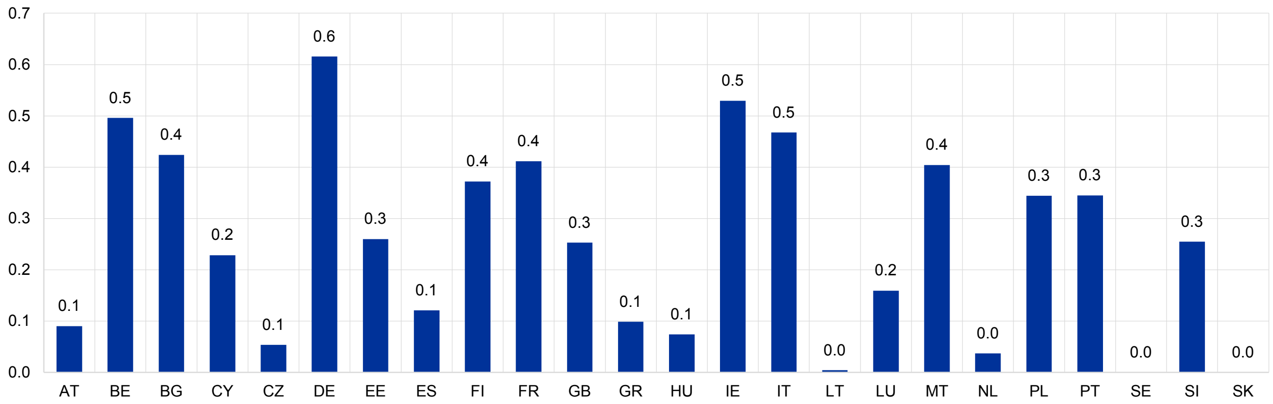
(ratios)



Notes: The reported multipliers are defined as the ratio of long-run real GDP responses relative to consolidated banking system nominal loan growth shocks. The underlying shocks to capital/leverage ratios are reported in Chart 11.1.

Chart 11.5

Cross-border to domestic response ratios (based on real GDP responses)



Notes: The ratio shown here is defined as the weighted foreign long-run real GDP responses relative to domestic long-run real GDP responses. The corresponding shocks to consolidated nominal loan growth under the asset-side deleveraging scenario are reported in Chart 11.1.

The estimates of the impact of shocks on real GDP (Chart 11.3) suggest that the asset-side deleveraging responses fall systematically below the empirical capital ratio shock scenario responses, and that the differences are sizeable from an economic point of view. The real GDP to loan growth multipliers (Chart 11.4) are indeed large for a number of countries, with ratios exceeding 0.5 for Austria, Germany, Finland, Slovakia, and a few other countries whose ratios are around 0.4. The GDP to loan growth shock multiples reflect the primary impact of the domestic loan supply as well as an additional amplifying effect provided by the loan supply from banks across borders, which leads to indirect trade spillover effects on the domestic economy. Apart from the cross-border amplification effect, which is a key feature of the model, the relatively sizeable GDP-loan multipliers are consistent with other findings from VAR-based studies, although they are somewhat larger than those normally produced by more structural and dynamic general equilibrium models.[97]

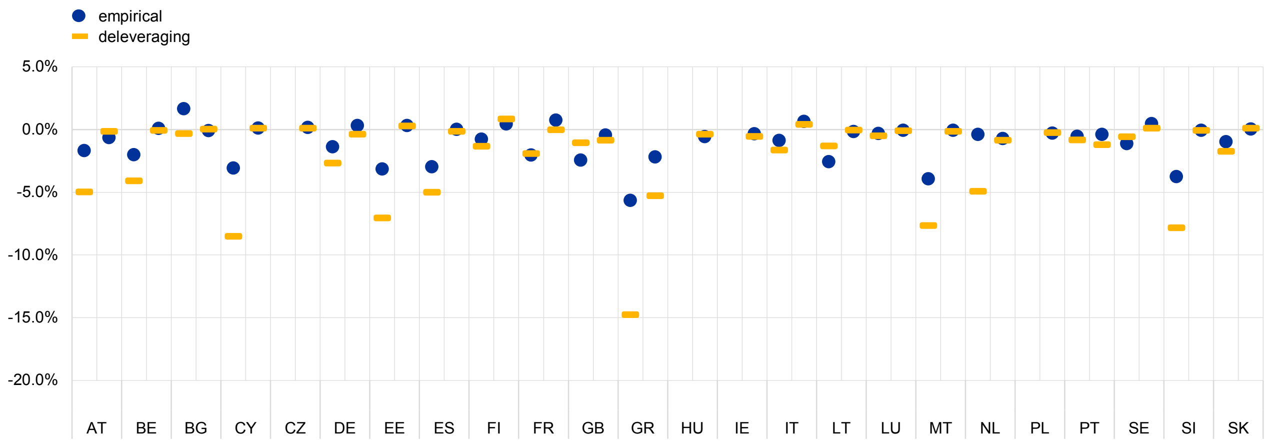
The cross-border to domestic effects ratios (Chart 11.5) suggest that shocks to the banking systems may, moreover, have sizeable cross-border effects. For instance, the ratio for the German banking system is estimated at about 0.6, the maximum across all banking systems. These ratios reflect again two combined channels of transmission: the cross-border credit supply of banks that are active abroad and cross-border macroeconomic feedback effects from bilateral trade channels.

The asset-side deleveraging scenario effects suggest quite adverse house price responses for the majority of countries whose banking systems are shocked (Chart 11.6). For some countries, such as France, it can be seen that the results of the deleveraging and the empirical shock scenarios are quite similar. In a few cases the empirical response of house prices is more negative than under the controlled full deleveraging scenario (see the responses for the United Kingdom, Lithuania, and Sweden).

Chart 11.6

Responses of nominal house price inflation to deleveraging shock scenarios

(natural log percentage points)



Notes: The responses are expressed as long-run log percentage point deviations from baseline growth. Both scenario types start from the same capital ratio shock per banking system. The left-hand column for each country reflects the domestic effects; the right-hand column reflects the weighted foreign effects.

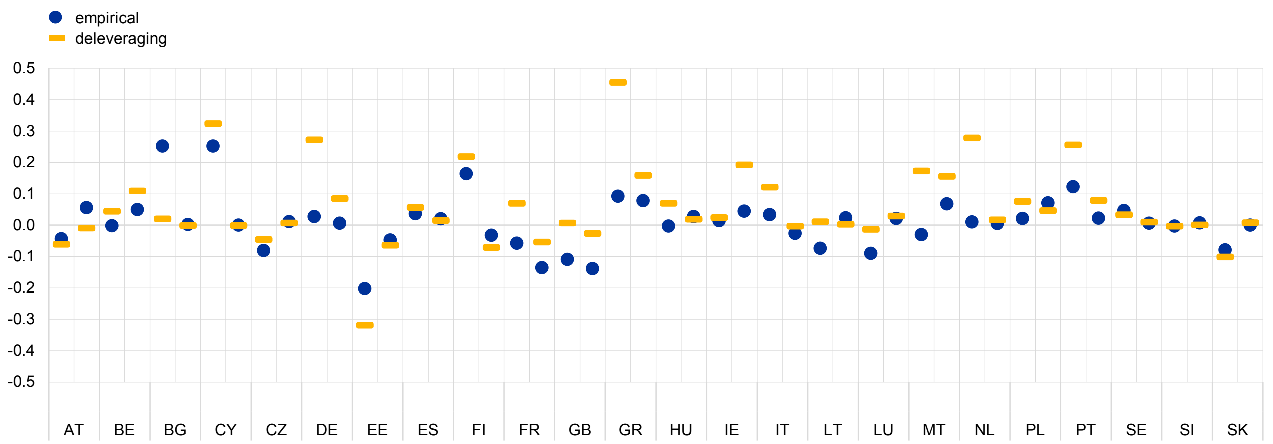
In many cases, loan interest rate responses (Chart 11.7) attain positive signs in the long run under the deleveraging scenario. It should be remembered that the responses at T=1 responses were constrained to be positive under the deleveraging scenario. In some banking systems the response signs revert in the long run, although they stay close to zero in most cases.

97 See, for example, BCBS 2010 for a discussion of the macroeconomic impact of capital requirements across a wide range of macro models, including VAR models, and why their outcomes may differ.

Chart 11.7

Responses of nominal loan interest rates to deleveraging shock scenarios

(percentage points)



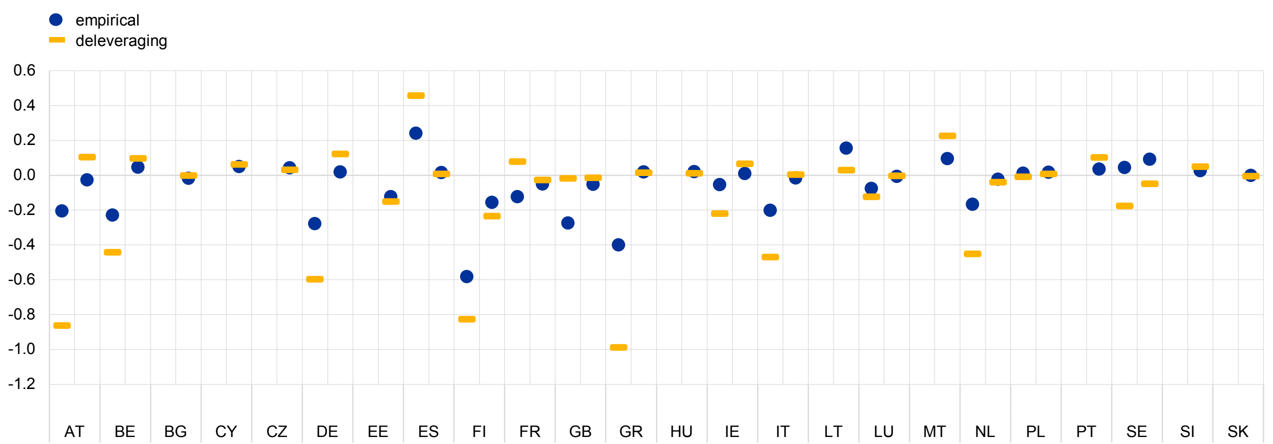
Notes: The responses are expressed as long-run percentage point deviations from baseline levels. Both scenario types start from the same capital ratio shock per banking system. The left-hand column for each country reflects the domestic effects; the right-hand column reflects the weighted foreign effects.

Turning to the impact on banks' probability of default (Chart 11.8), two aspects should be seen as the driving forces whose net impact may be either positive or negative. On the one hand, the PD of a bank falls mechanically the moment its leverage decreases (its capital ratio increases), all else – in particular asset volatility – being equal. Both scenario types imply downward pressure on PDs. On the other hand, banks' PDs may increase as a result of feedback through economic activity which, particularly for the full deleveraging simulation, is seen as contracting significantly. This drop in activity would imply higher asset volatility (reflecting, for instance, higher loan loss provisioning needs) which would imply some upward pressure on the PD of a bank. Which of the two effects dominates is an empirical question.

Chart 11.8

Responses of banking system probabilities of default to deleveraging shock scenarios

(percentage points)



Notes: The responses are expressed as long-run percentage point deviations from baseline levels. Both scenario types start from the same capital ratio shock per banking system. The left-hand column for each country reflects the domestic effects; the right-hand column reflects the weighted foreign effects.

For banking systems such as Austria, Belgium, Germany, Finland, Greece, Ireland, Italy, Netherlands, and Sweden (to list the more clear-cut cases) the estimated net effect on bank PDs is negative under the deleveraging shock scenario, i.e. the macro feedback effects on banks' PDs appear to be limited. By contrast, in other banking systems, such as Spain and France, the macro feedback effects appear to dominate, resulting in higher bank PDs. Notably, many of the banking systems that fall into the first category (i.e. a negative net effect on bank PDs) are characterised by relatively low capital ratios at the start of the simulation, specifically Belgium, Germany, Finland, Netherlands, and Sweden. It appears that, in terms of the lowering of bank PDs, more highly leveraged banking systems gain more from the mechanical reduction of leverage, with macro feedback effects not being large enough to outweigh that gain. This suggests that the benefits of increasing the level of bank capital measured in terms of higher bank resilience (proxied here by bank PDs) are greatest when capital ratios are initially low, whereas the beneficial impact may be somewhat less for higher initial capital ratios.

For a large-scale model of the kind presented in this chapter, it is important to conduct numerous robustness checks, for instance in respect of the structure imposed, as outlined above. As previously mentioned, the model has not been estimated in a completely unconstrained manner for two reasons: it would exhaust the degrees of freedom for the model to be practically no longer estimable and, in addition, it is desirable to keep a structure in the equations to reflect certain economic rationales. In that respect three specific alternative specifications have been considered to gauge the sensitivity of the scenario responses. The three specifications worth considering are (see Table 11.1 for comparison): i) to allow interest and deposit rates to exert a direct impact on the GDP deflator, using a global channel; ii) to allow the GDP deflator to exert a direct impact on banks' prices for loans and deposits, using a global channel; and iii) to allow loan volumes at the bank/banking system level to influence directly the loan interest and deposit rate measures, using, once again, a global channel.

On the basis of these alternative settings, the two scenarios were first re-simulated to obtain the cumulative responses of all model variables from the three alternative global models. The ratio between the cumulative responses for all countries and variables to the responses from the "base model" (previously introduced) was then computed, for only the subset of responses that were significant at a level of at least 20% in the base model. Under the base model, only a small part (less than 3%) of the significant cumulative responses, with regard to both domestic and cross-border responses, change their sign under the alternative model variants. The multiples suggest that the cumulative responses are, on average, close, with median multiples equalling just 1.02 across variables.

4 Conclusions

This chapter has presented a large-scale semi-structural model for the purpose of assessing the impact of changes in bank leverage and credit supply on real economic activity in EU countries. The model is based on a GVAR structure that is augmented to feature the presence of multiple cross-sections – countries, banks and central banks. In its current form, the MCS-GVAR comprises 28 EU economies along with a sample of 42 significant listed European banking groups. An alternative model variant based on aggregate banking system data was developed in parallel to the individual bank version, covering all 28 EU banking systems. Variables at the bank/banking system level – loan volumes, loan interest and deposit rates, leverage ratios and banks' probabilities of default – are combined with real and nominal activity measures at the country level.

Two types of scenario simulation were conducted using the model: a full asset-side deleveraging scenario, seen as an illustrative polar case, and an "empirical" scenario where banks consider a mixture of capital raising and balance sheet shrinkage. The results suggest that economic activity could drop significantly under the full deleveraging scenario. The empirical scenario, on the other hand, produces mixed, though on average somewhat negative, responses for real activity across countries. There are pronounced differences resulting from the two scenarios in many cases and this has important policy implications. In order to counteract any adverse economic response to the introduction of higher capital requirements, the macroprudential authority could for instance decide that the new capital requirements must be met by raising capital by a specific minimum target amount, or it could set a RWA floor for deleveraging.

The simulation results suggest, moreover, that cross-border, cross-bank and banking-system effects may be significant in many cases. Cross-border spillover effects are due to one of two features, or a combination of both: banks are active across borders and countries trade with one another. For an assessment of the possible effects of capital-based macroprudential policy instruments, a model like the MCS-GVAR is useful since it allows cross-border implications to be gauged, under the assumption that banks will adjust their lending behaviour to any markets to which they are exposed. More nuanced simulations may be conducted where, by making assumptions or through additional risk-return considerations, loan business in some countries reacts more or less than in others.

The mixed-cross-section feature of the GVAR is not only useful for an application involving individual banks. When operating with aggregate banking systems, the MCS structure is also relevant and is probably superior to the traditional GVAR with variable-specific weights. The reason for this is that the MCS-GVAR allows weights to be *equation*-specific as well as variable-specific. For example, for the loan growth equations in the system this means that economic activity variables can be weighted on the basis of loan exposure profiles, as they should be, and not on the basis of trade, as is the case for the traditional GVAR (even with a variable-specific weighting scheme).

The MCS-GVAR model framework can be combined with other elements of the stress test and macroprudential assessment toolkit, as illustrated in Chapter 3. The combined toolkit helps to assess the costs and benefits of macroprudential policy measures on a broader basis than using only supervisory data or aggregate sectoral estimates.

In the future, the aim is to further refine the identification approach to disentangling bank credit demand and supply, for example by augmenting the model with some non-bank credit volumes and/or prices that could serve as substitutes for bank credit (considering, for example, corporate bond volumes or prices, or other non-bank aggregates). Non-bank aggregates can be constrained such that they substitute bank supply, i.e. in the case of a full deleveraging scenario, for example by constraining non-bank credit volumes to expand and their prices to fall.

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ESTIMATING CONTAGION IMPACTS

Chapter 12 Interbank contagion

By Grzegorz Hałaj[98]

The interbank market was one of the main victims of the financial crisis that started in 2007. The crisis led to a general loss of trust among market participants and resulted in severe interbank market disruptions and even periodic freezes of certain market segments. Moreover, failures of some key market players triggered concerns about risks of interbank contagion whereby even small initial shocks could have potentially detrimental effects on the overall system. Fears about the potential for contagion were fuelled by uncertainty about "who is connected to whom". Ultimately, the consequences of the initial financial contagion also reached the real economy. As a result, macroprudential authorities have, in recent years, recognised the importance of contagion risk monitoring and have introduced various measures that aim to mitigate (and even better, reflect) the risks inherent in the bilateral links between banks in the interbank network.

Network tools can be integrated in the framework of the stress testing of individual banks to measure contagion in the event of stress, as defined by the stress testing scenario. In the most straightforward application, it can be assumed that banks experiencing a capital shortfall in the stress test would not be able to repay their interbank obligations. This could trigger a chain of second-round defaults of their counterparties along the interbank network linkages should interbank losses and those related to the stress testing of individual banks substantially erode their capital buffers.

The chapter presents tools and their application for the assessment of interbank contagion risk. The tools are useful to analyse direct and indirect channels of contagion related to banks' insolvency, i.e. those that are related to direct exposures between banks and those that are of a more behavioural nature as fire sales and asset portfolio overlaps. A variety of data sources is used to illustrate the complexity of contagion, which is rich in triggering and propagating mechanisms and whose analysis suffers from limitation in data availability. Notably, other complementary topics in cross-sector spillovers and contagion related to liquidity are covered in Chapters 13 and 14.

1 Contagion mechanism

The modelled assessment of the size of interbank contagion is based on what is known as the interbank clearing payments vector, derived by Eisenberg and Noe (2001). The clearing vector p^* reflects interbank payments in equilibrium after some banks have defaulted on their interbank payments following exogenous shocks,

98 Partly based on Hałaj and Kok (2013) and Battiston et al. (2016).

taking into account banks' buffers. In the modified version employed here, the clearing vector p^* is obtained from the following equation:

$$p^* = min\{max\{C - a + l + \pi^T p^*, 0\}, l\}$$

where

- C is a vector bank's regulatory capital. It reflects the full absorption capacity of the bank;
- a is a vector of interbank assets;
- l is a vector of interbank liabilities;
- transposed matrix of the relative interbank exposures with π_{ij}entry defined as bank *i* interbank exposure towards bank *j* divided by the total interbank exposure of bank *i*.

The equilibrium equation has a clear interpretation. The component *C* − *a* + *l* can be interpreted as banks' own funding sources adjusted by net interbank exposures. Interbank liabilities *l* are a proxy for a buffer set aside in the assets, assuming that banks keep some liquid sources to cover the potential outflow of interbank funding. Any decline in this buffer can be introduced via a shock to capital, *C*.

The ultimate interbank payments are derived as the equilibrium of flows in the interbank network. The contagious default on interbank deposits is detected by comparing $l_i$and p^* – if the difference is greater than 0, it means that bank *i* defaults on its interbank payments. The loss for the interbank creditors is calculated as
$loss = \pi^T(l - p^*)$
and can be normalised in terms of the risk-weighted assets (REA) to derive the basis-point change in the capital adequacy ratio (CAR)

$$\Delta CAR_i = 100\left(\frac{CT1_i - loss_i}{REA_i} - CAR_i\right)$$

In an event-driven concept of contagion, it is interesting to break down the first and second-round effects of contagion. First, the notion of a triggering bank is introduced, i.e. a bank that initially defaults on its interbank deposits (due to some exogenous shock not encompassed by the model). Second, the first-round effects are defined as those related purely to the default of banks on their interbank payments, given:

- a default of a triggering bank (or group of triggering banks) on all its interbank deposits,
- all other banks declaring they will pay back all their interbank debts.

Third, the default of other banks following triggering banks' inability to pay back their interbank debts would be classified as second-round contagion effects if:

- they will pay back all their debts if all non-triggering banks which are their debtors repay their debts,

- they are not capable of paying back part of their interbank deposits in the clearing payments equilibrium.

Usually, for the macroprudential analysis, the set of defaulting banks is defined using some macro-financial stress testing scenarios, which are translated into the first-round solvency position of banks. First, all banks' capital buffers are depleted following the usually adverse scenarios, which means that their contagion loss absorption capacity is weakened. Second, those banks that show their capital ratios falling below a certain threshold (for instance the 4.5% CET1 capital ratio) are assumed to default on their interbank payments. Illustrations are given in sub-section 4.

The critical component of the approach is the matrix of bilateral exposures. In some cases (see Section 3), the exposures may be available, for instance, reported by banks. In such cases, the uncertainty about the structure of linkages is limited to their variation in time due to the normal business process, for instance, related to changing liquidity needs. However, frequently, the structure of matrix π is uncertain given the data limitation (e.g. only large exposures are reported) or the lack of information on linkages other than the aggregate exposures of financial institutions towards all their (financial) counterparties. In such cases, random sampling techniques are useful.

Uncertainty about the exposures can also be useful in defining the distribution of contagion losses or as a proxy for the likelihood of the contagion spreading. Therefore, the measure of contagion losses, i.e. changes in capital ratios, ΔCAR, are presented as percentiles of the distribution with respect to the random structure of the interbank exposures. The distribution is obtained by means of Monte-Carlo simulation methods which, for large networks, can be extremely computationally exhaustive.[99] To define the randomness in the network structure, the concept of a probability map is introduced, enabling the interbank networks to be randomly sampled in a consistent manner.

1.1 The probability map of interbank exposures

Bank-by-bank bilateral interbank exposures are not readily available. For this reason, to define the probability structure of the interbank linkages (a probability map), as a starting point, the EBA disclosures on the geographical breakdown of individual banks' activities are used (here measured by the geographical breakdown of exposures at default). The probabilities were defined at country level, i.e. the exposures were aggregated within a country and the fraction of these exposures towards banks in a given country was calculated. These fractions were assumed to be the probabilities of a bank in a given country making an interbank placement to a bank in another (or the same) country.

[99] The current implementation entails the High Performance Computing (HPS) power of MATLAB to conduct simulations in a parallel mode. For example, it takes about 20 minutes to process one stress testing scenario for 100 bank systems and 20,000 simulations of network structures on ten cores.

The probability map can be interpreted as a prior for the likelihood that a link for a given pair of banks exists.

The analysis is based on random networks, whereby banks were grouped into two sub-categories: those with a domestic scope of activities and those with international activity. Banks within the same group were assigned similar average probabilities in the probability map. The classification was based on a ratio calculated as the proportion of cross-border intra-EU exposures to total exposures. With reference to the definition of internationally active banks, different threshold values were tried and the most robust specification appeared to be a proportion of international exposures to total exposures of 25 per cent. The classification of banks into the two sub-categories and the averaging of the probabilities of interbank connections reduce the estimation error when using only a single snapshot of data.

Different data sources can be used to compute the probability map. The probability map, based on public disclosures, is an arbitrary choice contingent on the rather limited availability of data about interbank market structures.[100] A concept of market fragmentation along the national borders, while treating the internationally active banks separately, seems to be justified. Nevertheless, the results (structure of the network and contagion spreading) are dependent on the particular probability structure (geographical proximity matters). Section 5 presents sensitivity analyses to illustrate how the probability map affects the systemic importance of a given bank.

2 Indirect channels of contagion

Direct exposures usually have limited potential to transmit contagion, as observed recently, for example by Glasserman and Young (2015). Several additional mechanisms have been identified that may substantially amplify the contagion losses, which are referred to as indirect channels of contagion.

Indirect contagion occurs when firms' actions generate externalities which affect other firms through non-contractual channels. Clerc et al. (2016) distinguishes two families of such channels. First, the market-price ones that arise because the liquidation of a given asset adversely affects its prices, and therefore all players exposed to such assets. Such liquidations, in particular forced liquidations, also called fire sales, may also give rise to liquidity problems (via collateral revaluation) and may consequently undermine solvency (via recognised losses in mark-to-market portfolios). Second, information channels also operate, as bad news or rumours may trigger hedging behaviour by direct and indirect counterparties to the distressed firm.

These indirect channels of contagion are the outcome of significant endogeneity. They often operate simultaneously, interacting with each other with potentially nonlinear effects, frequently stimulated by binding capital and liquidity regulatory constraints (see, for example, Cifuentes et al., 2005). The indirect effects are potentially most detrimental when financial institutions hold similar assets, i.e. a large

[100] The topic of data sources in covered in Section 3.

overlap in balance sheet portfolios can be observed (Caccioli et al., 2015). These indirect channels are likely to interact with the direct contagion channel, too, leading to systemic outcomes that are more severe than if only one contagion channel had been operational.

2.1 Fire sales

The concept of the sequence (p^n) is helpful in introducing the "fire sales" mechanism to the interbank equilibrium. In order to meet their obligations, banks may need to shed part of their securities portfolio; the fewer interbank assets they receive back, the higher the liquidation need. This may adversely affect the mark-to-market valuation of their securities portfolios and further depress their capacity to pay back their interbank creditors. Consequently, this mechanism may lead to a spiral effect of fire sales of securities (as, for example, suggested in Geanakoplos, 2009, and Brunnermeier, 2009). Greenwood et al. (2012) use fire sales in a systemic risk analysis of banks' behaviour, as they target leverage ratios after an exogenous shock has hit their capital buffers.

Banks may respond in different ways to the losses on interbank exposures depending on their strategies and goals. In order to cover the resultant liquidity shortfall, they may simply shed some assets. However, the sell-off may be much more severe for banks targeting their leverage ratio (see also Adrian and Shin, 2010). In the latter case, the usually double-digit ratio of "x" would translate into securities disposal of "x $*$ loss". The modelling framework of fire sales accounts for both cases.

One possible specification of the fire sales mechanism may be based on the assumption that the liquidity shortfall from interbank losses has to be covered by the liquidation of assets. The extent of the devaluation of securities portfolios is assumed to relate to the proportion of the liquidated securities to the total volume of securities held by banks. In order to quantify these fire sales, use is made of an auxiliary measure of the conditional amount of securities sold by bank *i* given that all banks pay back *p* units of their interbank deposits, i.e.:

$$SecSold(p) = \sum_{i=1}^{N} min\{S_i, (p_i - l_i)^-\}$$

where $x^- = -min\{x, 0\}$ and is called a negative part of *x*.

The new equilibrium interbank payments vector can be computed with a new loss absorption capacity which is equal to the initial capital level less the devaluation of the securities. Let TS denote the aggregate volume of securities held by the banks in the analysed system. Following the idea of Cifuentes et al. (2005), in order to relate the price of securities to the supply of these securities (equal to the volume of the fire sales) we introduce the α > 0 elasticity factor. Then the market value of securities is defined as:

$$S(p) = S \cdot exp\left(-\alpha\frac{SecSold(p)}{TS}\right)$$

The term $S - S(p^*)$ reflects the additional negative impact of selling securities at fire sale prices on the loss absorption capacity of banks following the interbank contagion.

2.2 Overlapping portfolios

The overlaps are banks' exposures to the same risk factors. The overlapping portfolio contagion channel deals with the risk of banks (firms) being exposed to very similar asset classes. The bigger the overlaps, the higher the systemic impact of a shock to a given asset class might be. For instance, the shock can be related to fire sales of the assets of defaulting banks that are subject to liquidation. The overlapping portfolios channel does not appear in isolation. It should rather be understood as one of the channels with the potential to severely amplify contagion effects. Notably, a correct understanding of the scale of the overlaps can facilitate the definition and calibration of the fire sales elasticity of liquidation prices (taking into account the liquidity of the item at stake, market liquidity and size in general)

The scale of portfolio overlaps is quantified by analysing the banks' leverage ratios to various asset classes (see Battiston et al., 2016). The inverse of the leverage ratio means the maximum loss, as a percentage of total assets, that a given bank can withstand. This notion can be further developed, by breaking down total assets into the bank's various exposures towards specific assets classes related to sectors, countries, instruments or counterparties. As a result, the notion of leverage network proves very useful. Banks are connected to various common asset classes, which creates a network of leverage described by a leverage matrix.

Specifically, in the context of the group of the largest EU banks, the leverage matrix is a simple mathematical instrument which can be used to characterise bank exposures towards the economic sectors of each country. Each of the elements of such a matrix corresponds to the leverage of a chosen bank, which is computed by dividing the invested capital by the bank's equity, vis-à-vis a specific country/sector pair. Leverage is an important tool for assessing a bank's exposure as it makes it possible to calculate the relative loss in the bank's equity based on the size of the shock hitting the real economy.

3 Data

3.1 Aggregate balance sheet information

The key data component of the contagion assessment covers the aggregate information on banks' balance sheets. This includes aggregate interbank lending and borrowing, capital buffers and measures of riskiness of assets (REAs). Supervisory data collections are the most reliable and frequent, although market coverage may be limited, as in the case of European banking supervision's focus on the largest banks in the euro area. Notably, similar aggregate data can also be found in the public domain, e.g. in banks' financial statements, increasing their availability and mitigating confidentiality issues with the publication of results. However, useful detailed breakdowns may not be accessible as, for instance, secured and unsecured interbank lending may be reported jointly.

Supervisory reporting is helpful in gauging banks' portfolio overlaps. European banking supervision's supervisory data, 2014 and 2016 confidential data collected for the purpose of the EU-wide stress testing exercises, IBSI data and ECB Securities Holding Statistics are particularly useful since they offer either rather granular portfolio or sub-portfolio level information, further broken down geographically. In particular, the supervisory data are very useful in offering a NACE code breakdown of exposures, i.e. providing insight into banks' exposures versus the rather granular economic sectors per country.

3.2 Large exposure limit data

The data on bilateral exposures between financial institutions is valuable since it provides information about the topology of the connections between institutions in the market and limits the need to employ estimation techniques to approximate unavailable linkages. Reporting of exposures classified as large exposures and payment system information are particularly useful sources of data.[101]

One of the network approaches to studying contagion transmission among the largest EU banks is based on European banking supervision significant institutions' fourth quarter 2015 reporting of large exposures to other financial institutions, and is described below.

To create the network of interbank exposures, COREP templates C27 (for counterparty identification – all counterparties classified as a credit institution) and templates C28 and C29 (for original exposures and exposure values after credit risk mitigation techniques) are employed.

Creating the network is challenging owing to the low quality of banks' large exposure reporting. For instance, not all banks provide the "credit institution" identifier in their reported data. Furthermore, the names of reported counterparties often differ across reporting entities and thus need to be carefully mapped and allocated. In addition, banks frequently do not report counterparty LEI codes or they only partially fill in the templates. However the biggest shortcoming is that these data include only exposures that meet CRR and EBA requirements for large exposure reporting.

[101] The Target 2 payments system gives the opportunity to use payments system data to calibrate the contagion models with the advantage of being available at high (even daily) frequency. Nevertheless, this advantage has to be weighed against the contamination of the payments system data with information not related to the direct exposures between banks (e.g. settlement and liquidity-related payments) and against the imprecision of the estimation of exposures from payment flows which are directly observed in the payments system. Therefore, the focus is on the large exposure limit data.

3.3 Credit networks and contagion risk involving the real sector

Potential spillovers between the real sector and the financial sector are a valid concern for macroprudential policy assessment. The interbank network contagion is extended by accounting for the links between banks and the large non-financial corporate sector. These are both the banks' exposures to corporates (lending of banks to large firms) and bank-based funding of firms, thus both lending and funding channel contagion can be captured.

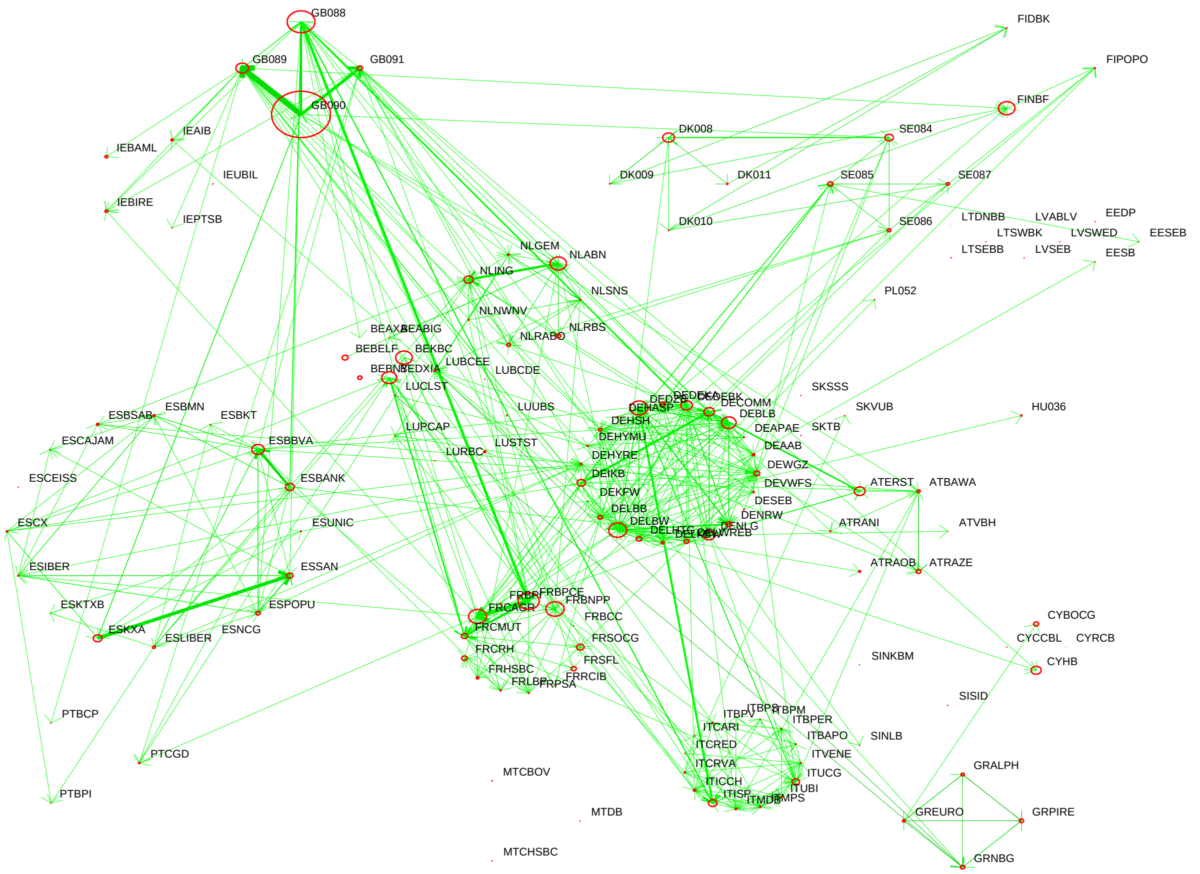
The exposures between banks and firms are simulated based on the available detailed aggregate information and using a refined random matching algorithm developed by Hałaj and Kok (2015). The input data for the model largely consists of public data on banks and firms other than banks, while also making use of some confidential credit register-based information about the average number of banks that provide funding to non-financial corporate firms, broken down by sector and country.[102] The algorithm is based on the accept-reject concept; links are drawn from a uniform distribution on the set of all potential links and they are accepted with a prior probability derived from supervisory data on geographical breakdown of banks' exposures to financial institutions.

Data on individual firms is based on official statistics and market data. The sample of non-bank firms is derived from the members of the benchmark equity indexes in EU countries. In total, market price and balance sheet data for around 900 firms from the blue chip indexes of the major stock exchanges in the EU have been collected from Bloomberg. In the applications so far, the in-sample companies constitute more than 75% of the total listed non-bank firms in the analysed countries in terms of total assets. In addition to the total asset figures, country and NACE sector codes, information on the companies' total liabilities, total equity and measures of credit risks were collected. As regards credit risk measures, the CDS spreads on senior debt with five years' maturity and long-term issuer ratings by Moody's, Fitch and S&P were collected. Where CDS information was not available, the average expected default frequencies (from Moody's KMV) within one year for a corresponding country and NACE code of the company were assigned to a company.

[102] These averages help to proxy the degree distribution of bank-firm links in the network, which are very basic and informative statistics of interconnectedness.

Chart 12.1

Simulated structure among largest EU banks



Notes: Based on the data from the 2014 Comprehensive Assessment. Thickness of a link proportional to the log (size of exposures); red circle proportional to log (total assets), arrows indicate direction of payment obligations of interbank exposures.

4 Simulations

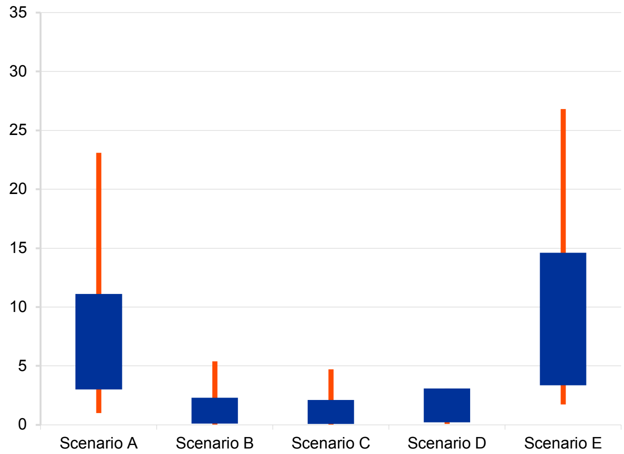
The structure of the interbank market in the EU can be visualized as in Chart 12.1 for one realisation from the whole distribution of network structures for the EU banking sector generated using the random network modelling approach. The chart has been structured in a geographical manner, i.e. entities are grouped by country and the corresponding cluster is assigned a position on the map that reflects the geography. The width of the arrows indicates the size of exposures (logarithmic scale) and the colouring scale (from light to dark green) denotes the probability (inferred from the interbank probability map) that a given bank grants an interbank deposit to the other bank. Most of the connections are between banks in the same country but the connectivity between the biggest domestic banking systems is also quite high (the German, Spanish and British banking systems, in particular). The chart suggests a two-tier core-periphery structure with highly connected domestic components and internationally active hubs that link banks' domestic subsets. Notably, the simulated structure is similar in topology with the observed ones (i.e. based on the EBA ad hoc data collection on the EU interbank market at the end of 2011).

The propagation of contagion in the model of the interbank market of the largest EU banks is illustrated by applying a macrofinancial scenario similar to the one used in the context of the Financial Stability Review of the ECB. In the analysed example, the contagion effects are found to be very limited but some market price and information channels that may play a role are not accounted for in the simulations. They are lower than one-fifth of a percentage point of additional CET1 capital reductions; even in the worst cases of the interbank network structure, they do not exceed 30 basis points. The upper ranges of the distribution of the system-wide CET1 ratio reductions are very close to zero under three out of five of the selected scenarios, reflecting the result that the banks which fall short of the minimum capital requirement would not trigger further defaults among the EU banks. As expected, it is under the combined shock scenario that system-wide CET1 ratio reductions in the upper ranges of the distribution reach the highest level – albeit with a very contained reduction of about 30 basis points (see Chart 12.2). This result reflects a high level of diversification of interbank exposures, as well as limited aggregate exposure to the countries where banks are projected to fail.

Chart 12.2

Reduction in the CET1 ratio due to interbank contagion without fire sales

(basis points, axis description)

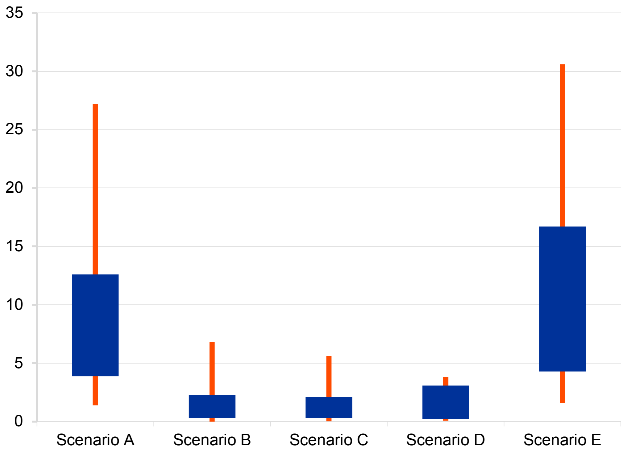


Note: Interquartile range represents the 25th to 75th percentiles of the cross-country contagion effects under the most severe (upper 10th percentiles) of the 20,000 simulated interbank networks.

Chart 12.3

Reduction in the CET1 ratio due to interbank contagion with fire sales

(basis points, axis description)



Note: Interquartile range represents the 25th to 75th percentiles of the cross-country contagion effects under the most severe (upper 10th percentiles) of the 20,000 simulated interbank networks.

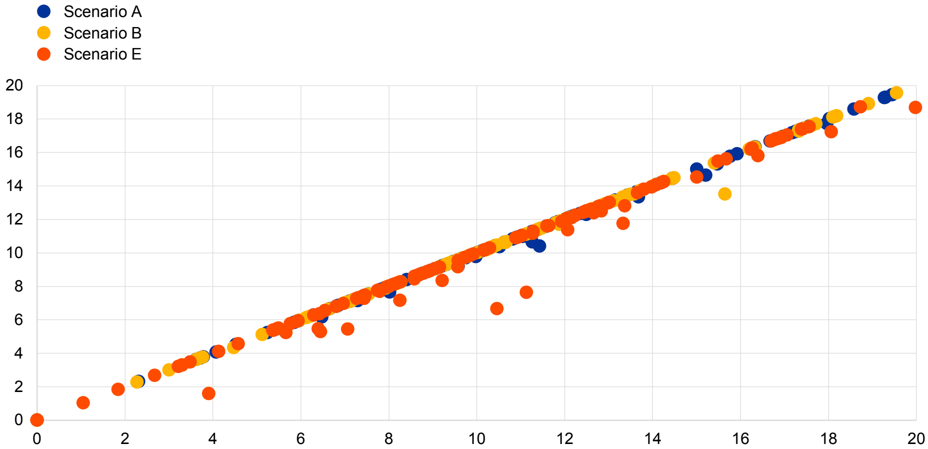
Adding the fire sales mechanism increases the estimates of contagion but to a limited extent (see Chart 12.3). The price impact of the securities selling is measured by an exponential function of the aggregate volume of liquidated securities in the system, calibrated to reflect the findings of Eser and Schwaab (2013) who estimated country-specific price elasticities to EUR 1 billion volume traded of sovereign securities. Consequently, the maximum loss amplification impact of fire sales is no higher than a few additional basis points of the CET1 ratio. Nevertheless, it needs to be emphasised that only one channel of direct interbank contagion, which has been fading out since the crisis, is activated in the model and that the fire sales are treated in a mechanistic way without potential amplifiers such as herding behaviour.

Moreover, such contagion effects appear to be hitting the EU banking system in a rather narrow-based manner. This is illustrated in Chart 12.4, which shows the additional ("second-round" contagion) impact on the stressed CET1 ratios of the individual banks in the sample due to the propagation effects within the interbank market following the initial solvency shocks under the adverse scenarios. Notably, the application of contagion analysis in the context of the macroprudential extension of 2016 EU-wide stress test (see Chapter 3) indicated similarly limited interbank contagion losses.

Chart 12.4

Individual banks' CET1 ratios following "first-round" and "second-round" (interbank contagion) effects of selected adverse scenarios

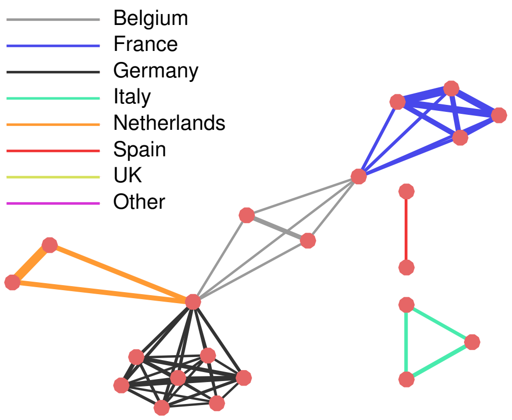
(capital adequacy ratio after first round (x-axis) and including the contagion losses (y-axis))



Notes: Interbank contagion results under the most severe (upper 10th percentiles) of the 20,000 simulated interbank networks.

Chart 12.5

The networks of overlapping exposures among banks towards the household sector



Notes: Based on Corep/Finrep supervisory statistics. Lines of a given colour represent exposures to the household sector in a given country, while the thickness of the lines indicate the degree of commonality of exposures per unit of equity between two banks (indicated by red dots). Width of lines proportional to the log of exposures.

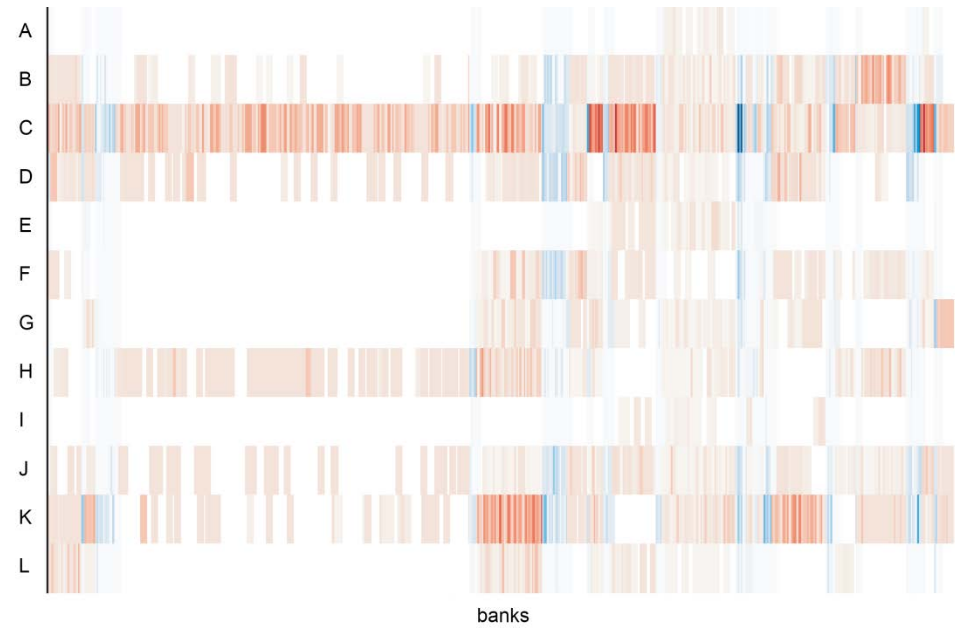
Turning to the assessment of the contagion potential stemming from the overlapping portfolios of the largest EU banks, a graph approach can be used to illustrate the leverage overlaps for certain sectors in Europe. The idea of the leverage overlap is to capture the common loss per unit of equity between any two banks due to an exposure to a given sector in a given country. The weightings of links between banks are computed as the minimum of the two banks' leverages vis-à-vis the chosen country/sector. These weightings correspond to the common relative loss in equity when a shock hits the system. For a given sector and each pair of banks, only the link corresponding to the country where the portfolio overlap is the highest is shown. In Chart 12.5 a few clusters of banks with common exposure in their own domestic household sector in Germany and France can be observed. The sector of credit institutions is the second largest exposure in total.

Contagion transmission from the real to the banking sector can be analysed in some counterfactual simulations of a shock to the creditworthiness (i.e. the PD) of different industry sectors simultaneously across all countries, and then use the model to derive the impact of contagion losses of the banks in the network (measured in terms of the banks' capital losses).

The results of this simulation are reported in Chart 12.6 (see Halaj, G. et al, 2015). There are material differences across sectors in terms of the contagion effects they may inflict on the banking sector (the darker red of the columns representing banks in the spectral chart indicate higher contagion-induced losses to bank capital). For example, whereas a shock to the manufacturing sector appears to have a widespread contagion effect on banks throughout the EU, similar shocks to the construction and real estate sectors mainly have material negative implications for banks in some isolated countries; notably, in countries where banks in recent years (especially pre-crisis) have built up considerable exposures to property developers and construction firms. Shocks to the energy sector are, in turn, found to produce considerable contagion effects on banks in the Southern European countries. Summing up, the results show the significance of the contagion channels involving the real sector. Therefore, its monitoring is particularly important from a macroprudential perspective and the proposed network-based approach proves to be quite effective in depicting country and sector differences.

Chart 12.6

Contagion impact on banks: shock to industry sector uniform across all countries



Notes: Changes in capital ratio (colour-coded) for each bank presented; A = agricultural, B = mining, C = manufacturing, D = energy, E = water, sewage, waste, F = construction, G = trade, H = transportation, I = accommodation/food, J = communication, K = financial, L = real estate. The intensity of a colour reflects the depth of the decline of in the capital ratio

5 Challenges and way forward

The development of contagion tools has accelerated in recent years, and researchers and policy makers are trying to address two issues to make the tools more useful and robust; one relates to data scope and availability and the other to capturing the indirect contagion channels.

Since financial integration has created a global financial system with cross-border and cross-market activities, the correct representation of the interconnectedness has to take into account global linkages between the main financial players. Policymakers and regulators have been improving the legal and institutional framework for adequate data collection. For instance, under the European Market Infrastructure Regulation, trade repositories in the EU collect comprehensive information on derivative trades. There are also ad hoc initiatives to close or minimise information gaps, where necessary; for instance, the Financial Stability Board global data collection on Central Counterparties and their linkages with clearing members and service providers. However, further harmonisation of definitions and databases is needed to allow for an efficient analysis across jurisdictions and product types.

One of the most crucial and general findings of the contagion analysis conducted since the outbreak of the financial crisis in 2007 is the importance of the indirect channels via which shocks propagate and are amplified. The first extensions of contagion models to cover amplification mechanisms, as discussed in Section 3, focused on a link between regulation and fire sales, indicating the significant potential of leverage to magnify contagion losses. Currently, the biggest challenge concerns the incorporation of certain strategic behaviours, for instance optimised behaviour by asset managers in restructuring their balance sheets, either following a shock or change in expectations, optimal responses by banks to liquidity risk and liquidity regulation, or responses by agents to changing financial structures such as CCP-based clearing.

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Chapter 13 Cross-sector contagion

By Maciej Grodzicki and Rui Silva[103]

The global financial crisis has highlighted the importance of understanding and quantifying shock propagation mechanisms both within and across countries. Most stress test exercises capture first-round effects stemming from adverse but plausible macroeconomic scenarios but do not take into account the non-linearities that characterise systemic risk and its implications from a shock amplification perspective. Against this background, identifying the channels and linkages through which local shocks may be transmitted elsewhere remains critical from a macroprudential perspective. Such spillovers as reported in Chapter 3, for example, may be assessed using financial network analysis at the bank level (see Chapter 12) as well as at the country and sectoral levels.

As part of the top-down stress test analytical framework developed by ECB staff, this chapter describes the methodology underlying a cross-sectoral contagion framework using financial account data for institutional sectors and countries in the euro area. Results from this tool serve various purposes, such as identifying country or sectoral exposures at risk under an adverse scenario, or estimating contagion effects at the sectoral and country level.

Importantly, the presented methodology assumes that second-round effects are exclusively driven by mark-to-market transmission mechanisms which operate over a very short time horizon, while endogenous reactions (i.e. the responses of economic agents via a rebalancing of their asset holdings) are not taken into account.

The rest of the chapter presents the data that have been used, the main mechanisms at play and finally the illustrative results.

1 Networks: description of the data

The cross-sectoral analysis uses euro area sector accounts (also known as flow of funds statistics) at both the individual country and the euro area levels. These statistics provide the financial and non-financial accounts of the different economic agents grouped according to the European System of Accounts (ESA 2010) methodological framework.[104] In this context, economies are considered to be composed of nine main and distinct sectors: households (HH), non-financial corporations (NFCs), banks and other monetary financial institutions (MFIs), insurance companies (INS), pension funds (PF), other financial intermediaries

[103] With input from Fabio Franch and Sara Testi.

[104] The ESA 2010 is a Regulation of the European Parliament and of the Council (Regulation No 549/2013) and sets compulsory methodological standards, definitions, classifications and accounting rules for European national accounts statistics. Market prices are ESA's reference for valuation.

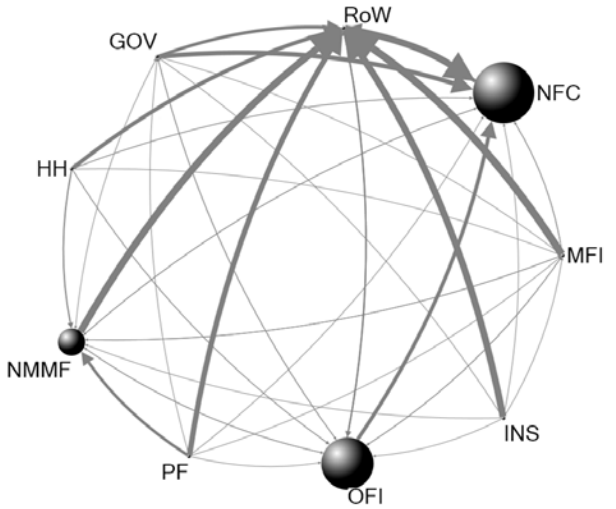
(OFIs), non-money market investment funds (NMMFs), government (GOV) and the rest of the world (RoW).

A useful feature of the dataset from a contagion perspective is that these groups are interconnected via reciprocal holdings of financial instruments issued by a given sector, thus forming a closed and internally consistent system. In other words, each financial asset item of a sector has a counterparty item on the liability side of one other sector. The financial networks used in this analysis can thus be summarised as a set of nodes, each economic sector, with several links between them, reflecting bilateral cross-sector exposures.

At the same time, at the sectoral level, financial account data do not always provide information about the specific counterparties of the instruments issued by a given sector (known as "who-to-whom" accounts). However these data have recently been improved to provide detailed information on the counterpart sector of some of the instruments issued, showing positions for which the creditor sector (security holder) and debtor sector (issuer of the security) are simultaneously identified for a number of instruments.[105] When bilateral linkages are not readily available, various statistical procedures, such as maximum entropy techniques, which exploit the relative shares of the sector-specific total assets and liabilities, can be employed.[106]

Chart 13.1

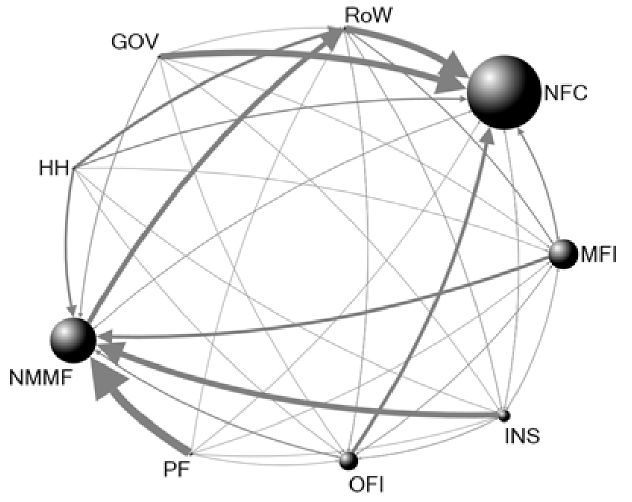
Equity holdings in country A, Q4 2015



Sources: ECB and authors calculations.
Notes: The direction of the arcs reflects the equity holdings of one sector by another sector, while the thickness of the arcs reflects the relative size of those holdings. The nodes reflect intra-sectoral equity holdings.

Chart 13.2

Equity holdings in country B, Q4 2015



Sources: ECB and authors calculations.
Notes: The direction of the arcs reflects the equity holdings of one sector by another sector, while the thickness of the arcs reflects the relative size of those holdings. The nodes reflect intra-sectoral equity holdings.

Charts 13.1 and 13.2 provide examples of financial networks employed in the contagion analysis, based on equity holdings, in two euro area countries. Bilateral exposure data are available for listed shares and investment fund shares/units, two

[105] These data are currently available for deposits, short and long-term debt securities, short and long-term loans, listed shares and investment fund shares.

[106] See, for example, Upper and Worms (2004), Lelyveld and Liedorp (2006) and Wells (2004).

out of the three instruments used to shape these networks. The matrix for the third instrument (unlisted shares) is estimated based on the distribution of holdings of listed shares. Overall, it is possible to identify relevant equity interlinkages across the financial and non-financial sectors in both countries, despite some clear differences in the network configuration. The implications of such features are important, *inter alia,* to understand the dynamics of shock propagation mechanisms.

Despite the marked reversal of European financial integration since the outbreak of the global financial crisis, cross-border spillovers and the transmission of shocks remain relevant. Largely on account of data limitations, this framework treats national financial sectors as closed. Therefore, one possible extension to it would be to account for connections between the already existing country-specific sector networks through cross-border banking linkages.[107] The euro area MFI balance sheet statistics provide detailed data about the financial exposures between banking sectors of euro area countries that could be used for that purpose.

2 Shock propagation mechanism

The data set presented in the previous section provides a way to assess the economic relevance of sectoral interconnectedness and can also provide information on the distribution of losses within the economy following an initial shock on the asset side of a sector's balance sheet. Importantly, sectors are assumed to be subject to mark-to-market accounting, meaning that if a sector experiences an adverse shock to the value of its assets, then this will also be reflected as a reduction in its own equity.

The basic intuition behind the shock propagation mechanism is that each financial instrument has both an issuer and a holder, so that equity losses in one sector are quickly transmitted to the balance sheets of other sectors via cross-holdings of shares.[108] The iterative algorithm calculates the distribution of losses in each sector for each round, according to the sizes of the balance sheet linkages with the sectors that were affected in the previous round. Theoretically, this process continues as long as: (i) some of the sectors report positive earnings that offset the initial loss; (ii) the shock reaches a sector which does not issue equity;[109] (iii) the affected sector's equity is reduced to zero.

Typically, this framework is used to assess the cross-sectoral impacts resulting from a decrease in the economic value of banks (proxied by the MFI sector) or insurers, caused by the reduction in book value of equity implied by an adverse macroeconomic scenario, at both euro area aggregate level and country level. Contagion analysis may be conducted under the assumption that several shocks would be triggered at the same time, for example with a common scenario impacting

[107] See Castrén and Rancan (2013).

[108] See Castrén and Kavonius (2009).

[109] For instance, households and government sectors typically hold large amounts of equity issued by other sectors, but they do not issue their own equity; therefore, these sectors do not transmit shocks further.

the equity values of banks and insurers simultaneously. Initial losses would then be amplified by equity cross-holdings between the two sectors, with the final impact determined by country-specific networks of these holdings.[110] In this application, it is useful to isolate the effect of each shock in order to identify and quantify the corresponding channels of propagation. The initial loss may also be more stylised instead of being based on a detailed macro-financial scenario, serving the purpose of sensitivity analysis rather than scenario analysis.

The proposed propagation mechanism, while powerful and drawing on a rich information set, rests, however, on a number of strong assumptions, in particular concerning the efficiency of stock markets. The most plausible course of future events, that is, a baseline scenario, is assumed to have already been reflected in the market value of equity. In addition, markets are assumed to have perfect foresight, and once the adverse scenario is triggered, investors would treat it as the most likely course of future events, thus immediately adjusting market prices downwards. In practice, this approach implies the price-to-book ratio remains constant while the adverse scenario materialises. This assumption may not be fully realistic when bank shares trade at a significant discount to book values, which indicates that investors may view the reported book values as overly optimistic and expect future losses that can partly overlap with the losses predicted under the adverse scenario of the stress test.

3 Ilustrative simulation results

Charts 13.3 and 13.4 illustrate a hypothetical shock propagation and convergence process for countries A and B, using the financial networks presented in the previous section. This simulation assumes, in both cases, a permanent impairment of loans extended by banks that causes a 25% mark-to-market drop in the value of shareholder equity. The results should be interpreted with caution, however, since sector accounts data are not consolidated which means that intra-sector exposures are also taken into account and, consequently, spillover impacts may be biased upwards.

There are important differences between the two economies in how the losses are propagated. In particular, the sectors that are initially most affected by banks' capital depletion in countries A and B are NMMF and OFI, respectively, therefore reflecting the largest holdings of MFI sector's equity shares. In subsequent rounds, the sectors holding sufficiently diversified portfolios (in particular, exposed to sectors that were hit in the first round) should be more affected. Furthermore, the results suggest that the convergence process happens faster in country A, i.e. around ten iterations. In the case of country B, however, this process takes slightly longer for some sectors (particularly NMMF and INS). These iterations should not be interpreted as a period

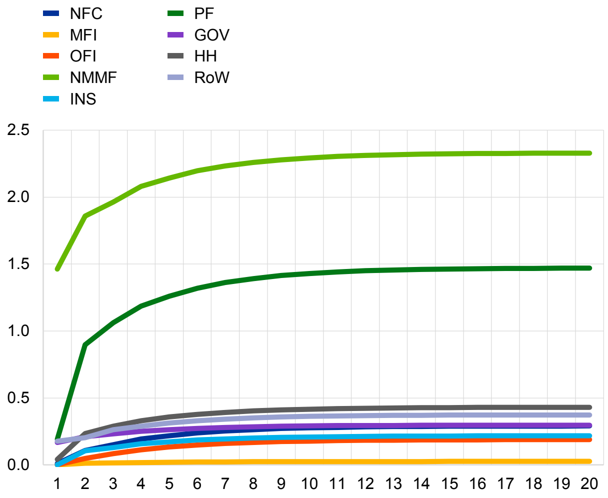
[110] As mentioned in the previous section, the cross-border linkages are not taken into account in this version of the tool; however, they are likely to play an important role in the transmission of financial shocks in the euro area.

of time over which cross-sectoral spillovers materialise, and where markets are efficient, such effects should occur instantaneously.

Chart 13.3

Shock propagation through country A's economy

(Q4 2015; x-axis: number of propagation rounds; y-axis: propagation losses measured as a percentage of financial assets of the sector; reported as cumulative sum)

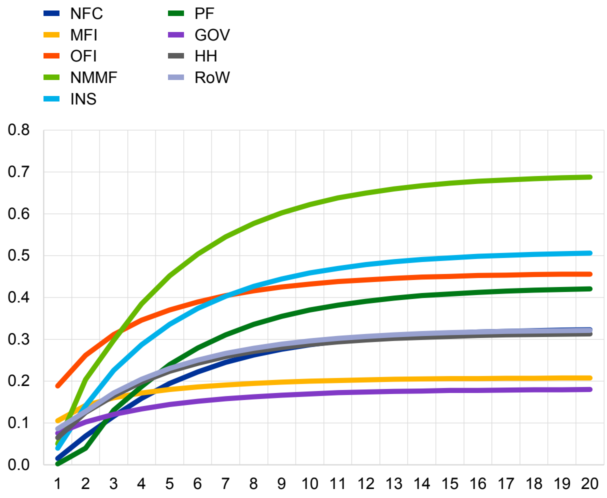


Sources: ECB and authors calculations.

Chart 13.4

Shock propagation through country B's economy

(Q4 2015; x-axis: number of propagation rounds; y-axis: propagation losses measured as a percentage of financial assets of the sector; reported as cumulative sum)



Sources: ECB and authors calculations.

The framework can be extended to capture the impact of the shocks to banks' asset values on the valuation of non-equity claims on the bank. Under the EU framework for the resolution of banks, should bank equity be fully depleted, losses would be imposed on creditors in line with their hierarchy. The riskiness of bank debt instruments would therefore increase after the adverse scenario materialises, and the market value – especially of subordinated claims that rank only one step above equity in the capital structure – would decrease, affecting the balance sheet of the debt investors. In this context, the sectoral distance-to-default framework presented in Castrén and Kavonius (2009) could be useful to provide an aggregate view of the impact of shocks to bank assets on the valuation of its capital and debt instruments.

Importantly, the current framework abstracts from endogenous reactions and macroeconomic feedback. As observed during the crisis, however, banks that were severely hit also deleveraged significantly, either by cutting down on new lending and/or selling assets. In a multi-period setting, rebalancing of balance sheets might be needed after such shocks materialise. Additionally, the deterioration in the real sector's balance sheets may lead to a contraction in investment and consumption, which would affect the macroeconomic conditions and feed back to the banking sector through lower profitability and higher credit losses. The framework presented could also be enhanced by the inclusion of a cross-border dimension. While introducing an extra layer of complexity, this would also allow for investigation of the spillover effects not only within but also across countries.

4 Conclusion

Understanding the architecture of the financial system, its time-variant nature and its role in the transmission of disturbances from one sector to the entire economy (or even beyond, across countries) is highly relevant from a macroprudential perspective. Since the onset of the global financial crisis, much attention has been devoted to the analysis of financial networks, as it makes it possible, inter alia*,* to estimate how the adverse impact of a given financial shock might spread along the bilateral linkages between firms and sectors. The analysis described in this chapter provides a way to quantify these features at both the country and sectoral levels, and, ultimately, helps generate policy recommendations which focus on mitigating the repercussions of such shocks.

There are several ways in which the current framework can be enhanced. This chapter explored one of those options. The current cross-sectoral contagion framework is limited to simulating domestic shocks and propagation mechanisms. Nevertheless, future work is envisaged to include a cross-border network, exploring in particular the already available data on cross-border linkages of national banking sectors. The extension that would capture the effects of equity price shocks on the valuation of debt instruments issued by banks and other financial institutions would also improve the coverage of potential contagion channels. Another extension may focus on the evolution of cross-sector and cross-border linkages over time. This would shed light on the time dimension of spillover risks and on the response of the financial sector to shocks.

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FURTHER EXTENSIONS

Chapter 14 A top-down liquidity stress test framework

By Grzegorz Hałaj and Dimitrios Laliotis[111]

The aim of this chapter is to gain a better understanding of the most important components of the top-down liquidity stress test framework that is being developed by ECB staff for macroprudential purposes.

A top-down stress testing framework with a macroprudential orientation needs to treat banks' liquidity and solvency conditions in an integrated manner. Experience from past crises reinforces the view that liquidity crises may precede the emergence of a solvency crisis or magnify the effect that a severe solvency stress in the market may have on liquidity. Moreover, evidence on the magnitude of amplification effects and negative externalities during past crises related to the reactions of banks to external shocks and to the behaviour of other market participants further strengthens the need for a framework that is able to fully account for such impact.

Such a framework is to materially enhance the ability of macroprudential authorities to (i) measure and assess the amplification effects of funding shocks via fire sales, interbank linkages, overlapping asset portfolios and cross-holding of debt channels, and (ii) capture deteriorating funding conditions for individual banks linked to their solvency conditions or the availability of unencumbered collateral.

It is also important to consider the fact that liquidity and solvency are usually treated separately, both in terms of their decoupled regulatory treatment and in terms of the differing stress testing approaches. After the financial crisis, there is a need to review them in parallel and to treat liquidity issues consistently and on the basis of their two-way interactions with solvency issues. For macroprudential purposes, both have to be assessed as system-wide in order to be relevant.

However, achieving this poses a number of challenges. Liquidity crises, for instance, are "low frequency-high impact" events. Consequently, models are based and calibrated on very small historical data sets and often require judgement calls on how liquidity-related events might materialise in the future. This makes the development, application and evolution of the liquidity stress test framework a rather challenging task, since it is often necessary to capture the impact and magnitude of potential future liquidity crises in a world that has been radically transformed, from an institutional and regulatory point of view, in response to the most recent global liquidity crisis.

[111] Some of the models presented in this chapter are based on the work done by Miha Leber, Oana Maria Georgescu, Javier Población and the authors in the context of liquidity shortfall analysis for macroprudential purposes.

While there have been already a number of EU-wide solvency stress tests exercises, there has been no EU-wide liquidity stress test exercise to fully evaluate and assess the performance of the existing framework of models in a real large-scale environment. Therefore, the maturity of the models that comprise the liquidity stress test framework should not be seen in direct comparison with the maturity of the solvency stress test models that have been gradually evolving in terms of sophistication, based on valuable feedback from the industry since the 2011 EBA stress test. The work on further development and enhancement of the calibration is ongoing.

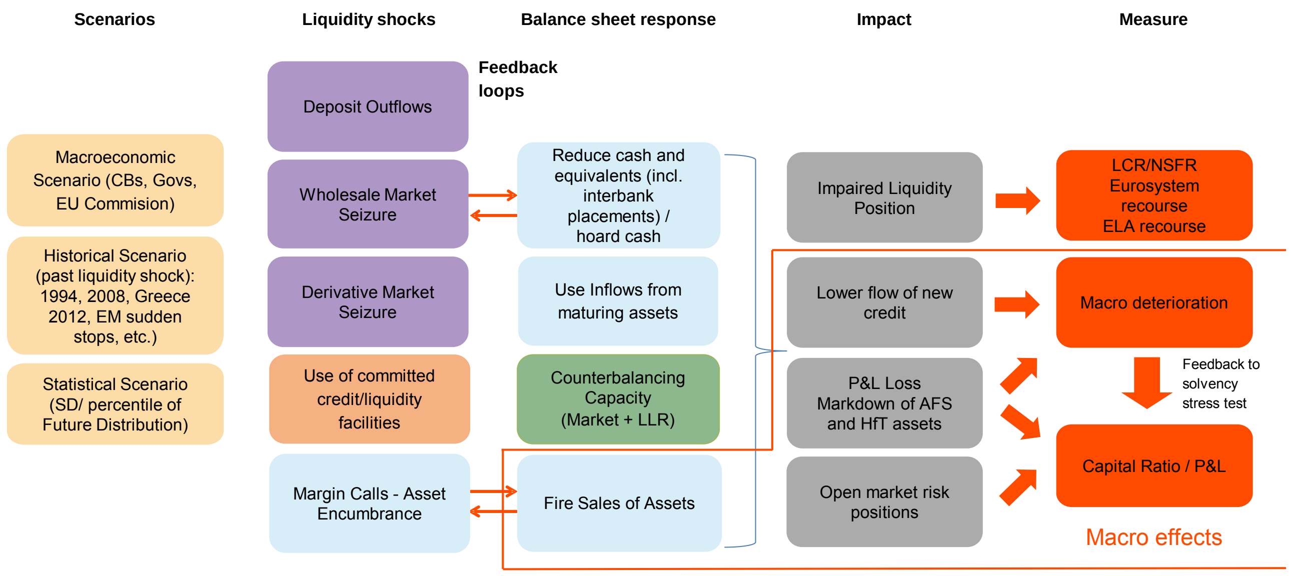
1 Introduction

This chapter presents the basic building blocks of the top-down liquidity stress test framework with some illustrative results of its application. The framework consists of two complementary pillars: (i) a granular and data-rich balance sheet module that deals with bank-level data on funding mix and liquid asset composition, and (ii) a modular systemic model pillar that integrates the functionality required to capture the impact of system-wide amplification mechanisms and negative externalities.

This modular functional architecture is illustrated in Chart 14.1. The red box corresponds to functional requirements that are linked with the systemic/macroprudential pillar of the top-down liquidity stress test framework.

Chart 14.1

Modular functional components of the top-down stress test architecture



The top-down liquidity stress test framework builds upon balance sheet-based principles, where funding stress is applied in the form of scenario-based run-off rates for the liability side, and counterbalancing capacity is measured by the appropriate calibration of haircuts on the available total liquid assets (TLA) of each individual bank.

This highly granular balance sheet composition dataset lays the groundwork on which systemic core modules and models must be superimposed to account for second-round or contagion effects on funding and market pricing transmission channels. Thereby, the systemic attributes of the liquidity stress test exercise can be assessed by appropriately calibrating the impact of asset fire sales under a stress scenario or the effects of network topology and interconnectedness in amplifying funding run-offs, while preserving the rationality and pragmatism of the balance sheet assumptions on which the systemic models are based.

The modular design is carefully selected to accommodate new features and extensions, such as the explicit modelling of the existence of the lender of last resort, interbank or cross-country spillovers, solvency and liquidity interlinkages, scenario flavouring, and sensitivity analysis that would be needed in the context of a joint solvency-liquidity top-down stress test. Emphasis is placed on enhancing the system-wide orientation of this approach by introducing network-based tools and incorporating some behavioural elements of agent-based models to better capture the systemic aspect of liquidity risk. Moreover, a very granular level of analysis of banks' counterbalancing capacity aims to capture the additional externalities associated with the shortage of sufficiently unencumbered collateral in a disaggregated manner, since it is believed that liquidity impairment – even in fragments of the entire market – may have a significant impact on contagion and (partial) market freezes.

The following section presents illustrative results that were obtained using the top-down liquidity stress test framework with only part of the systemic modules activated. While the results are based on a mostly stylised and partial application of the framework, they are indicative of the overall strength and capacity of the framework and of the additional insight that the systemic angle can provide to the macroprudential authority or the macro modeller.

2 The basic framework approach and data repository

The impact on the liquidity of individual banks is assessed under different stress scenarios in terms of (i) the magnitude of funding freezes, and (ii) the availability of liquidity buffers to counterbalance liquidity outflows. The scenarios are defined with increasing degrees of stress severity and applied to both the availability of funding and the level of haircuts that banks may face in using their liquid assets to replenish liquidity outflows.

For this purpose, a four-step approach is applied:

(i) Replication and calibration of banks' funding mix;

(ii) Application of progressive stress scenarios impacting funding availability;

(iii) Estimation of banks' counterbalancing capacity to respond to liquidity stress by quantifying their available liquid assets in each stress scenario. Appropriate haircuts are applied in each scenario to reflect discounts associated with asset sales or an increase in the collateral haircuts;

(iv) Estimation of liquidity shortfall/surplus by comparing projected liquidity needs with available liquidity buffers for each individual bank.

The main data source used in the analysis is supervisory reporting data (FINREP/COREP[112] bank submissions), which was used to infer both the liability (funding mix) and asset (TLA) sides of the exercise. Recent data on asset encumbrance[113], including the collateral received in secured lending, were also incorporated to further enhance the accuracy of the assessment of banks' counterbalancing capacity and to assess potential dependencies of asset encumbrance level and liquidity stress.

Maturation profiles and the breakdown of credit ratings by sovereign debt holdings are used as in the EBA stress test exercise, based on the assumption of a slow change for these tenor and rating allocations.[114] The respective granular data on the tenor composition and credit quality characteristics of the non-sovereign part of the available-for-sale accounting portfolio can easily be incorporated in a similar manner. ECB data on the applicable securities haircuts may be used for the calibration of applied haircuts on the asset side, while centralised securities database (CSDB) and securities holdings statistics data may also generally be used for the calibration of liability run-off rates.

A set of 94 SSM banks was selected for the results presented in this chapter in order to ensure a reasonable degree of coverage and sufficiently good quality of the submitted data. Bank results may be aggregated by country, region, business model or size in order to produce a higher level system-wide liquidity assessment. Those aggregates may be monitored on the basis of regular data updates (FINREP cycle).

2.1 Scenario-based analysis

Three basic scenarios are used, with the most severe ("severely adverse") roughly corresponding to the market shock following the collapse of Lehman Brothers. Two milder scenarios ("mild" and "adverse") are also considered to simulate the effects of

112 FINREP F.01.01, F04.01, F04.01, F04.02, F04.03, F04.04, F05.00, F.08.01a, F32.01, F32.02a and C.01.00 were mainly used for the data collection.

113 Commission Implementing Regulation (EU) 2015/79 of 18 December 2014, amending Implementing Regulation (EU) No 680/2014, laying down implementing technical standards with regard to supervisory reporting of institutions according to Regulation (EU) No 575/2013 of the European Parliament and of the Council as regards asset encumbrance, single data point model and validation rules: http://eur-lex.europa.eu/legal-content/EN/TXT/?uri=uriserv%3AOJ.L_.2015.014.01.0001.01.eng

114 EBA 2014 stress test data are used in the results presented. Going forward, this input will be replaced by the information available from the EBA 2016 stress test exercise.

weaker but more plausible liquidity shocks.[115] Although there is no limit to the number of scenarios that can be considered (and, in practice, the model is assessed on a range of stress factor scenarios for sensitivity analysis purposes), identifying three scenarios as the most relevant ones simplifies the presentation of results and the conceptualisation of the proposed process.

Table 14.1
Liquidity stress scenarios

	Mild	Adverse	Severely adverse
Stress severity	0.25	0.50	1.00

Note: Severity = X times Lehman[116]

The analysis assumes that stressed liquidity conditions persist for three months. Therefore, all liquidity needs are rescaled to a three-month maturation window, which plays an important role in the calibration of applied run-off rates for long and short-term funding sources. In other words, liquidity needs are assumed to be higher for a short-term than a long-term funding source for a similar amount of notional funding. The run-off rates of funding sources are calibrated on the basis of a conservative estimate of funding that would mature or that would need to be rolled over during a randomly selected forward-in-time three-month window.

The severity levels of the above scenarios have an impact on:

- the run-off rates applied on the liability side (banks cannot fully roll over their maturing funding needs);
- the haircuts applied to liquid assets. These represent the limited efficacy of the relevant markets due to the prevailing stressed conditions that would require higher funding haircuts, either using assets of the same type as collateral (secured funding) or fire sale pricing, if funding is assumed on the basis of direct asset disposal.

The framework also examines greater stress impacts by allowing the severity of the scenario to go beyond the level of the severely adverse scenario. It also makes it possible to deviate from the almost linear stress factor mapping of the three basic scenarios to a fully parameterised non-linear functional form of the applied stress factors (either convex or concave). By setting the mild scenario to correspond to a stress factor of 0.25 and the severely adverse to correspond to a stress factor of 1, a simple non-linear functional form is used to define the scenarios between those points and beyond the stress factor of 1.

2.2 Funding sources and determination of liquidity needs

EBA stress test data are used to calibrate the maturity profile for each sub-segment of the wholesale market at individual bank level. More precisely, a "liquidity basis"

[115] The approach cannot be directly compared to the LCR, as it assumes a three-month stress horizon, as opposed to the one-month LCR one. Moreover, unlike the LCR, no stable inflows are assumed. However, some comparison with LCR can be made in terms of the severity of the assumed run-off rates, i.e. the LCR would fit somewhere between the mild and the adverse scenarios.

[116] Calibration of the stress factors follows the guiding principle that the severely adverse scenario should be mapped to market conditions following the Lehman's default. Relevant evidence from the existing literature is used to anchor run-offs and haircuts.

calculation for each wholesale market segment is conducted, taking into account maturities over the entire horizon for long-term sources of funds[117] and over the first quarter for shorter-term funding. In order to ensure a conservative estimation of the required minimum funding, a floor expressed as a percentage of the outstanding volume is defined at 10% or 20% for long-term funds and 60% for short-term funds. This is done to partially compensate for the fact that run-off rates are applied to the (lower) calculated basis and not to the full outstanding volume.

Liquidity needs for each bank are derived by applying run-off rates for the respective scenario to the estimated liquidity basis for the wholesale funding sources and the outstanding volume of deposits. Table 14.2 summarises the run-off rates for different sources of funding for each scenario.[118]

Table 14.2
Liability side run-off rates

Run-off rates		Mild	Adverse	Severely adverse	
Unsecured interbank lending	Unsecured interbank liabilities				
	Unsecured interbank assets				
	Net unsecured interbank liabilities	30%	65%	100%	Applied on calc. basis/Basis floored at 60% of outsanding volume
Secured interbank (and other financial institutions) lending	Secured interbank liabilities				
	Secured interbank assets				
	Net secured interbank liabilities	15%	30%	50%	Applied on calc. basis/Basis floored at 60% of outsanding volume
Own debt issued	Covered bonds	10%	20%	30%	Applied on calc. basis/Basis floored at 10% of outsanding volume
	Other own debt issued	30%	70%	100%	Applied on calc. basis/Basis floored at 10% of outsanding volume
Other wholesale funding	Certificates of deposit	30%	70%	100%	Applied on calc. basis/Basis floored at 60% of outsanding volume
	Structured products (e.g. structured notes)	30%	70%	100%	Applied on calc. Basis/Basis floored at 20% of outsanding volume
	Asset-backed securities	15%	30%	50%	Applied on calc. basis/Basis floored at 20% of outsanding volume
	Net other wholesale liabilities	30%	70%	100%	Applied on calc. basis/Basis floored at 60% of outsanding volume
Deposits - stable	Term + gov	3%	5%	10%	Apllied on outstanding volume
Deposits - non stable	Sight	5%	10%	20%	Apllied on outstanding volume

Note: These values are not directly comparable with LCR values because the purpose of this exercise is not to calculate regulatory liquidity requirements but to provide an idea of liquidity needs under several stress scenarios.

117 Liquidity stress conditions are infrequent and could come at any point in time. Therefore, a prudent estimate of potential funding that needs to be replenished should be used. While there are several ways to achieve that conservative estimate, one of which may be the analysis of micro-data of banks' securities and own debt issuance maturation schedule, the use of stress test data likely provides a decent proxy in terms of conservatism.

118 A more granular funding breakdown can be supported, provided that supervisory reporting data at such a level of granularity is available and that appropriate run-off rates may be defined at the more granular level in order to more accurately reflect liquidity shortfalls. Switching from net interbank secured and unsecured liabilities to dealing separately with the asset and liability sides might be the most obvious improvement in this direction. Furthermore, the split of corporate deposits into operational and non-operational deposits may also enhance the accuracy of the outflow calculation. Intra-group interbank exposures might also be a slightly more complex component of such treatment.

The increase in contingent liabilities (credit and liquidity commitments) and in the asset encumbrance levels for existing funding positions is muted in this analysis due to the lack of consistent data.[119]

2.3 TLA and determination of counterbalancing capacity

Basic information about TLAs is obtained mostly from FINREP data, while the capacity of banks to respond to liquidity stress is estimated by applying asset and scenario-specific haircuts to their liquid assets.

The following five categories of assets are considered for the calculation of TLAs:

- cash and central bank deposits
- sovereign debt securities
- other debt securities (non-sovereign, issued by financial corporations)
- other debt securities (non-sovereign, issued by non-financial corporations)
- equity securities.

Table 14.3
Non-sovereign liquid assets haircuts

	Asset side – liquid assets		
	Mild	Adverse	Severely adverse
Debt (corporate – financial corporations)	15%	25%	35%
Debt (corporate – non-financial corporations)	5%	10%	15%
Equities	25%	50%	75%
Cash + deposits with central banks	0%	0%	0%

Note: It is important to notice that these values are average values because, irrespective of a bank's home country, large banks may hold securities from the whole euro area, the exact breakdown of which may be not available at the required reporting frequency.

With the exception of sovereign debt securities, which are treated differently, all liquid assets are linked with explicit haircuts for each scenario (see Table A.3). As in the case of liabilities, this choice is not imposed by the framework but mandated by the need for simplicity. In a full-scale application, the most granular level of information could be enabled: this would suggest using stress test data on the actual composition of the non-sovereign bond portfolio in terms of both tenors/maturities and credit quality. Scenario haircuts for that level of granularity are calibrated in line with the ECB's expanded asset purchase programme (APP) haircuts for the mild scenario, appropriately scaled up for higher-stress scenarios. A similar principle may

[119] The framework makes it possible to analyse the impact of contingent liabilities and the increase in asset encumbrance for existing positions, provided that the scaling factors that capture such contingent increase in funding needs are defined on the basis of existing evidence and provided that certain assumptions are also made for the TLAs that will be used to account for the asset encumbrance increase.

apply to the equity holdings by further separating listed and non-listed holdings and appropriately adjusting applied haircuts in the boundary scenarios.

For sovereign debt securities, a more granular calculation of haircuts is sought, using data from the EBA stress test sovereign exposures template. Sovereign debt was broken down by issuers and remaining maturities.

For the mild scenario, an average haircut value has been selected for each credit rating[120] (see Table 14.A.1 in the Annex). In a second step, haircuts for the shortest and longest maturity are defined in a way that ensures a plausible term structure. Finally, the haircuts for intermediary maturities are computed by logarithmic interpolation, subject to the constraint that the average haircut defined at the beginning is obtained for the whole tenor curve. For the adverse and severely adverse scenarios, haircuts are calculated by using scaling factors of 1.2 and 1.5 respectively on the haircut that corresponds to the mild scenario for each credit rating. The approach for the mild scenario is used to obtain the haircuts across the maturity structure (see Table 14.4 for the general stylised scenario concept and Table 14.A.1 in the Annex for the specific calibration of haircuts used in the simulations based on tenor and rating class).[121]

Table 14.4
Sovereign liquid assets haircut scaling factor

	Mild	Adverse	Severely adverse
Debt securities (sovereign)	100%	120%	150%

The approach outlined above controls for the credit quality of the sovereign debt holdings of each bank when calculating the counterbalancing capacity of the TLA. This has a significant impact on the average haircut applied across countries, due to the fragmentation in sovereign debt markets and the tendency of banks to hold domestic sovereign debt in excess of the proportion of sovereign issuance.

2.4 Liquidity shortfalls/surpluses and related metrics

The projected liquidity needs are offset by the available TLA post haircut. The difference determines the liquidity shortfall/surplus for each individual bank under a given scenario.

Several metrics can be used to examine the results, and benchmark proxies are applied in order to assess the relative resilience of banks to liquidity stress:

120 Based on ratings from Standard and Poor’s.

121 The haircut treatment of sovereign holdings tries to map scenario-based projections of the secured lending conditions using a simple scaling factor for the projection of haircuts in the adverse and severely adverse scenarios and logarithmic interpolation for the calculation of haircuts for intermediary tenors. Although this approach may be regarded as simplistic in nature, the framework does not in general impose any restriction on choosing more complex haircut models or even using projections calibrated on the (albeit rather limited) instances of historical liquidity stress conditions. A more complex calibration approach based on anchoring haircuts to those applied by the ECB (based on the official list of eligible marketable assets) for each tenor bucket and credit rating has been developed for both sovereign and corporate bond issues.

- number of banks with a shortfall over total number of banks (percentage that will require liquidity assistance)
- absolute average shortfall over total liabilities
- total shortfall/surplus over total liabilities by country
- average TLAs over total liabilities (liquidity buffers)
- TLAs post-haircut over initial TLA (no haircut).

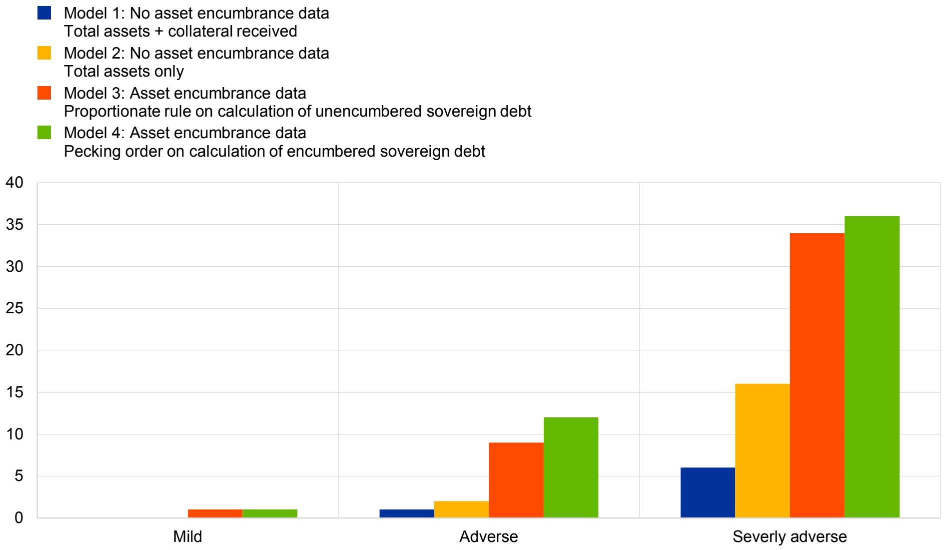
An important new metric has also been introduced and extensively used for cross-temporal assessment purposes here, namely the "distance to liquidity stress indicator (DLSI)". This measures the required stress factor that has to be applied for a bank to reach the point where it becomes illiquid (surpluses turn into shortfalls). Since the mild scenario corresponds to a stress factor of 0.25 and the severely adverse scenario to a stress factor of 1, any DLSI value below 1 suggests that the bank would face a liquidity shortfall before the severely adverse scenario. Conversely, a DLSI value above 1 would suggest that the bank has the counterbalancing capacity to withstand the stress that corresponds to the severely adverse scenario and additional stress would therefore be required in order for that bank to have a liquidity shortfall.

2.5 Results

Chart 14.2 presents some results on the number of banks that reach a stressed level under the three main scenarios for four models. The four models considered relate to different choices of the modelling approach as regards (i) the inclusion of asset encumbrance data in considering counterbalancing capacity, (ii) the treatment of the collateral received by counterparts, (iii) the optionality linked to the possibility that the bank may re-hypothecate to match liquidity outflows, and (iv) the different options that can be used as an assumption for determining the bank's policy on the "consumption" of available assets, i.e. the pecking order based on which they have already encumbered existing collateral. More specifically:

- Model 1 does not take into account any form of asset encumbrance and also assumes that the collateral received by the bank is part of the bank's TLA (full re-hypothecation).
- Model 2 does not take into account asset encumbrance and also assumes that the scope of TLA relates only to the bank's own assets (no re-hypothecation).
- Model 3 makes full use of asset encumbrance data and assumes a proportionate rule as regards the assets that have already been used for funding purposes ("pro rata" rule on encumbrance).
- Model 4 also makes full use of asset encumbrance data and assumes a certain value-maximising pecking order (i.e. best quality/lower haircut collateral is pledged first) to determine which assets become encumbered.

Chart 14.2
Banks with a shortfall

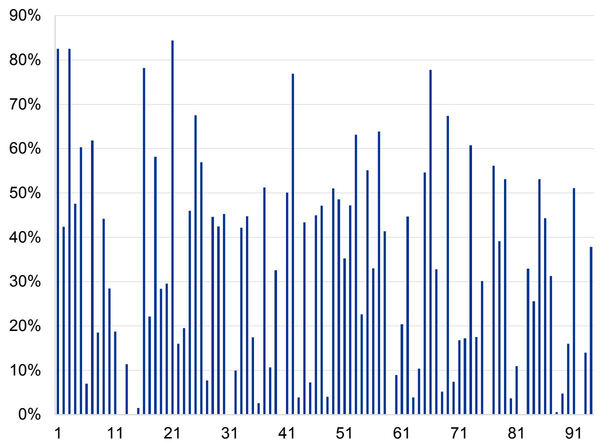


Sources: FINREP and ECB calculations.

It is apparent that asset encumbrance has a significant impact on the results, as the number of banks that reach the stress level in each scenario is significantly higher for those models that take asset encumbrance into account. With an average of approximately 47% of TLAs across the bank sample and a significant variance between banks (see Chart 14.3), asset encumbrance appears to be the driver that defines counterbalancing capacity to withstand liquidity stress. This finding, when combined with the diversity in the average haircut levels of TLA (i.e. TLA quality) (Chart 14.4), is the main determinant of TLA quality and adequacy.

Chart 14.3
TLA asset encumbrance levels

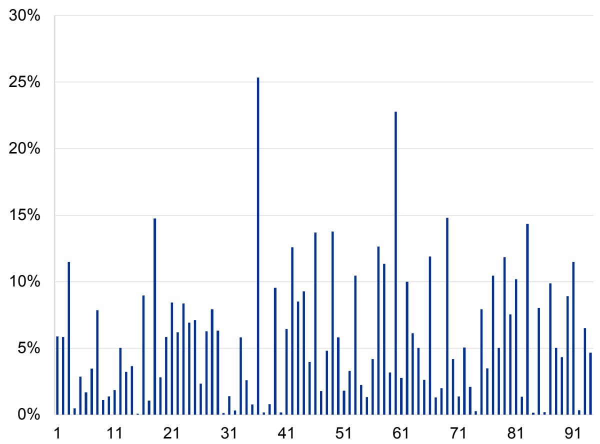
(all sample banks; asset encumbrance levels, percentage points)



Sources: FINREP and ECB calculations.

Chart 14.4
TLA average haircut levels

(all sample banks; asset encumbrance levels, percentage points)



Sources: FINREP, ECB and ECB calculations.

It is important to note that even for this stylised exercise a significant number[122] of banks fail both the adverse and severely adverse scenarios.

From an average shortfall perspective, the analysis suggests an improvement in banks' counterbalancing capacity when compared with a similar exercise conducted using a past date as the reference date, since banks appear to have significantly adapted their funding mix profile and asset composition. This may be attributed to an attempt to gradually comply with Liquidity Coverage Ratio (LCR) and Net Stable Funding Ratio (NSFR) requirements. Increased disclosures on the liquidity front may also have contributed to this.

Table 14.6

Average shortfalls as a percentage of liabilities

	Average shortfall as a percentage of liabilities		
	Mild	Adverse	Severely adverse
Proportionate rule	0.12%	1.94%	3.54%
Pecking order rule	0.91%	1.74%	3.50%

Sources: ECB and ECB calculations.
Note: Average is calculated across banks that have a total shortfall.

For banks that face a shortfall as a percentage of their liabilities, the average shortfall remains contained and is around 2% in the adverse scenario and 3.5% in the severely adverse scenario (see Table 14.6). The counter-intuitive reduction in the average shortfall in the pecking order option mainly relates to the fact that more banks are failing (with smaller shortfalls, on average) and are included in the averaging process. The total liquidity shortfall accounts for approximately €260 billion in the severely adverse scenario, but this smaller impact may also be linked to the fact that central bank funding of approximately €560 billion is not included in the simulations.[123]

As far as cluster analysis is concerned, Table 14.7 and Chart 14.5 present the respective aggregates for illustrative purposes based on a stylised clustering scheme[124] that was built for this purpose.

It is important to note that even with this simple clustering scheme, significant differences between cluster members can be observed in terms of their ability to withstand a liquidity crisis (see Chart 14.5). Cluster BM 5 appears to be the more resilient cluster, with significant amounts of excess TLA even in the severely adverse scenario; clusters BM4 and BM1 have significantly higher average DLSIs than those of clusters BM 2 and BM 3.

[122] Between nine and 34 banks fail in the model that calculates unencumbered assets using a proportionate rule and between 13 and 37 fail when a pecking order is assumed (encumbered assets as calculated based on a lower haircut principle). The proportionate rule model with asset encumbrance data will form the basis of any analysis that follows. The size of the sample was set to 94 banks based on the total number of SSM banks with adequate data on both sides (liability and asset encumbrance).

[123] Although part of this ECB funding may be assigned to liquidity shortfalls, it was included in the calculations in order to allow for an individual bank-by-bank assessment of the impact of the shortfall results.

[124] The scheme is based on a business model clustering principle and uses some balance sheet size (absolute asset size) and business orientation (local or global presence) indicators and expert judgement as regards the business model classification of non-standard entities.

Table 14.7

Business model clusters – number of failing banks and average shortfall/surplus

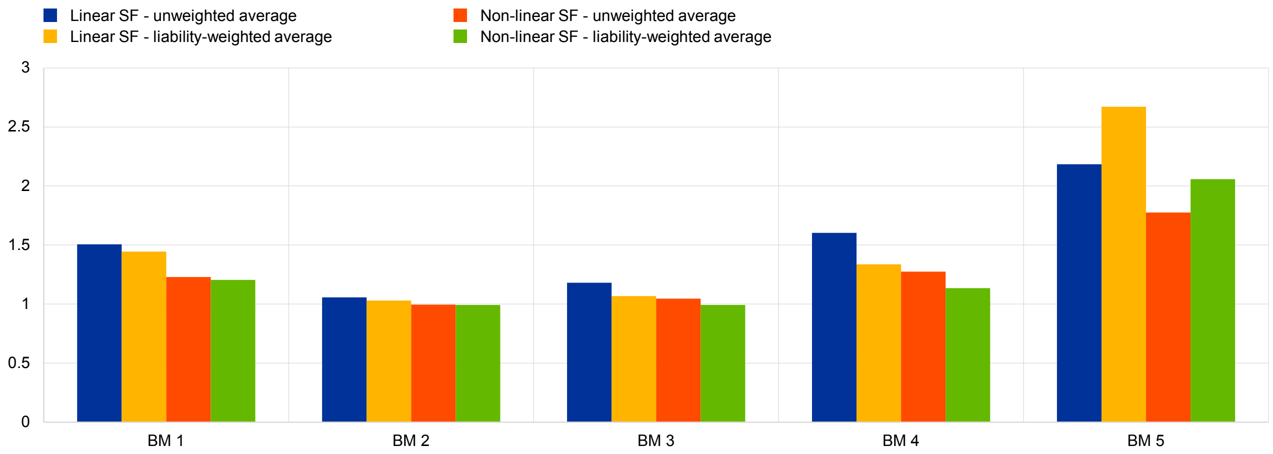
	Total banks	Failed			Total liquidity impact – TLA post-haircut			Shortfalls: total liquidity impact – TLA post-haircut			Surplus: total liquidity impact – TLA post-haircut		
					Mild	Adverse	Severely adverse	Mild	Adverse	Severely adverse	Mild	Adverse	Severely adverse
BM 1	12	-	-	5	12.06%	8.71%	2.50%	0.00%	0.00%	-1.28%	12.06%	8.71%	3.78%
BM 2	21	-	3	10	12.17%	7.88%	-0.07%	0.00%	-0.09%	-1.38%	12.17%	7.98%	1.31%
BM 3	21	1	1	10	10.84%	7.03%	-0.06%	0.00%	-0.13%	-2.22%	10.85%	7.15%	2.15%
BM 4	34	-	2	8	13.28%	9.25%	1.76%	0.00%	-0.33%	-1.90%	13.28%	9.58%	3.66%
BM 5	6	-	-	1	32.45%	27.40%	18.02%	0.00%	0.00%	-0.10%	32.45%	27.40%	18.12%

Source: FINREP and ECB calculations.
Note: Averages shown are total liability-weighted. A positive sign corresponds to a liquidity surplus and a negative sign corresponds to a liquidity shortfall. Simulation results are based on the proportionate rule, including asset encumbrance that includes collateral received but not pledged and the linear stress factor.

Chart 14.5

Business model clusters – distance to liquidity stress indicator (DLSI) (unweighted and liability-weighted average)

y-axis: DLSI – average stress factor required to bring the bank/cluster to liquidity stress

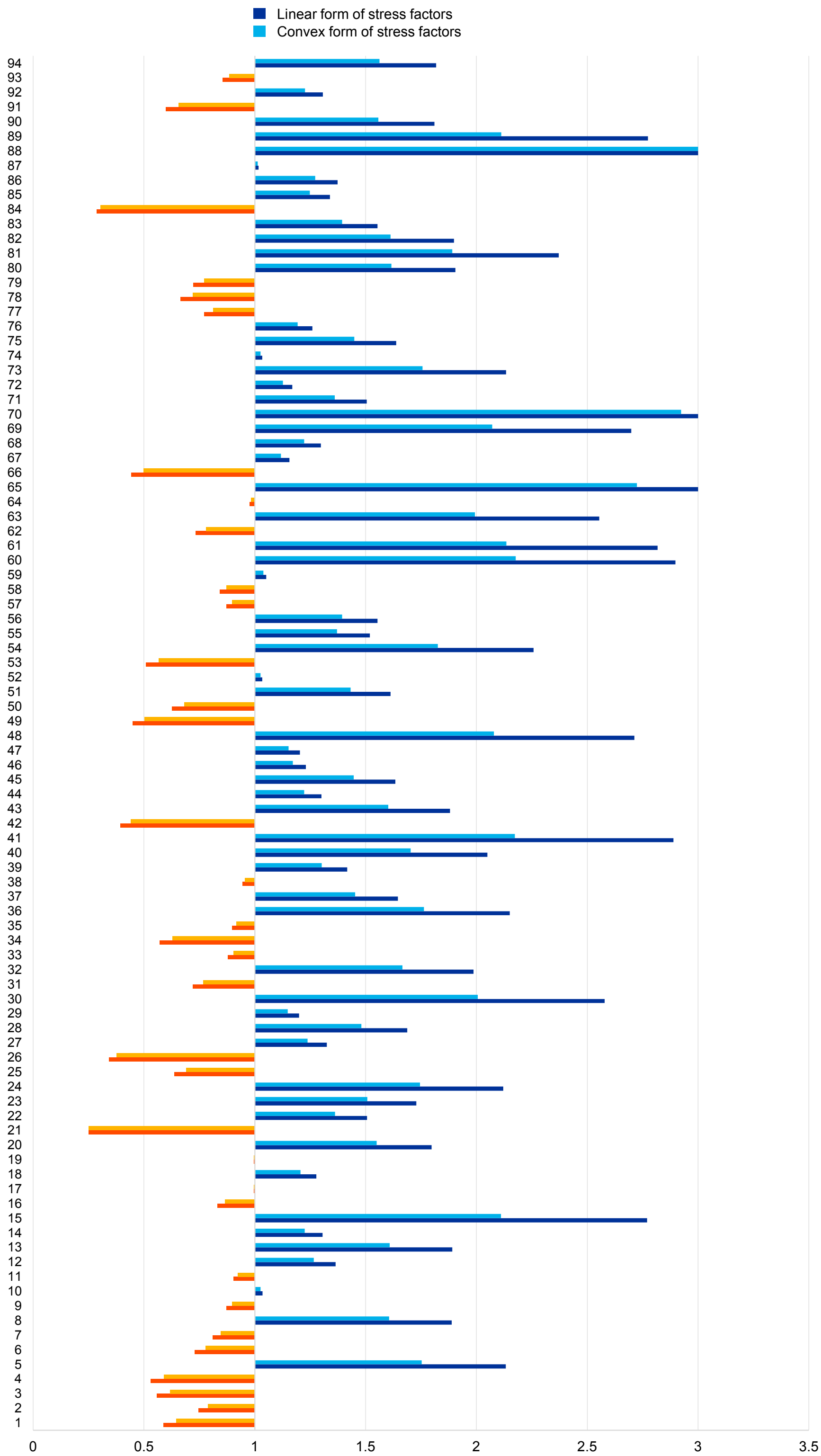


Sources: FINREP and ECB calculations.
Note: Simulation based on the proportionate rule and including asset encumbrance.

Chart 14.6

Impact of a linear or convex stress factor function on DLSI

All sample banks: DLSI in stress factor points



Sources: FINREP and authors calculations.
Notes: Orange and red bars correspond to banks with a shortfall in the severely adverse scenario in the case of convex and linear form of stress factors respectively. The simulation is based on proportionate rule and including asset encumbrance.

With respect to individual banks' capacity to withstand a major liquidity crisis, Chart 14.6 visualises the way that the DLSI metric can be used for monitoring and assessment purposes. The results for individual banks are presented for two modelling options: (i) the stress factors are kept linear (approximately in accordance with the three basic scenarios presented in this chapter with respect to the applied run-offs and haircuts), and (ii) the stress factors have a more convex functional form, although the mild and severely adverse scenarios are the same (which allows for a larger impact of stress factors that go beyond the severely adverse scenario).

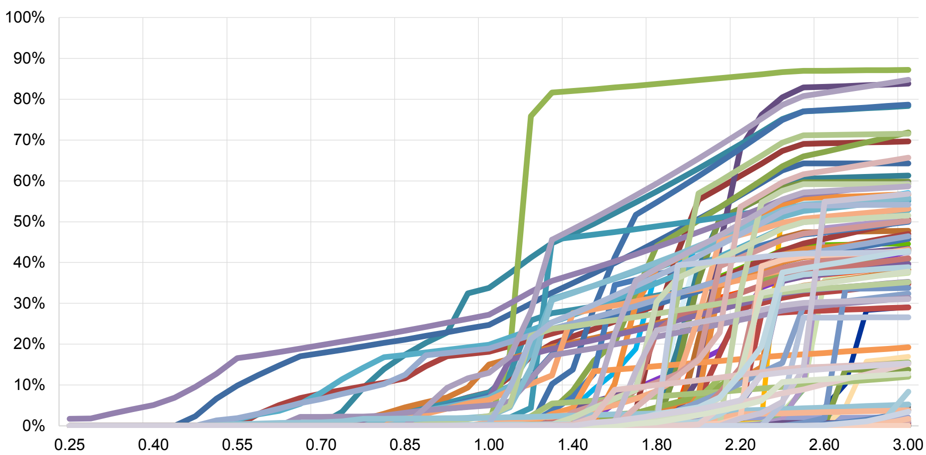
Banks with a DLSI below 1 (red and orange bars in the chart) will have a liquidity shortfall for a liquidity stress factor that corresponds to a scenario that is less severe than the severely adverse scenario, i.e. they practically fail the stress test. In contrast, banks with values above 1 (dark and light blue bars in the chart) can withstand liquidity crises that are more severe than the severely adverse scenario. The higher the DLSI value for a bank, the greater the strength of the bank in terms of counterbalancing capacity. The DLSI can also be used to measure changes in systemic risks with respect to liquidity, since by comparing bank-specific or system-wide DLSI readings over time (assuming quarterly updates using the same stress parameters), the current strength of the system to withstand a liquidity shock can be assessed.

Chart 14.6 also compares the DLSI outcomes of all individual banks in the sample for a linear and non-linear form of stress factors, attempting to depict the possible impact of non-linearities in the way that liquidity stress scenarios materialise.

Chart 14.7

Average TLA haircuts per bank and stress factor level

All sample banks: effective haircut on TLA, percentage points



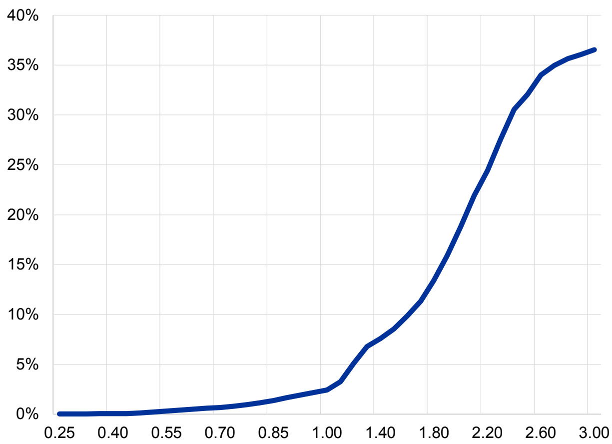
Source: authors calculations.

This is also shown in Charts 14.7 to 14.9, which present the average effective haircut on TLAs that the individual bank (see Chart 14.7) and the whole sample of banks (see Chart 14.8 for the average and Chart 14.9 for quantile statistics on increasing stress factors) face as the applied stress increases from 0.25 (mild) to 1 (severely adverse) and beyond. The apparent non-linearities and upside shocks on the effective haircuts that banks face under stress when combined with the non-linear form in which liquidity crisis materialise may need to be further investigated. The fact that encumbrance “resides” on the linear part of this curve (mild scenario) leaves little room for the system as a whole to avoid non-linear effects in the event of a more acute crisis.

Chart 14.8

Average TLA haircuts for all stress factor levels

Average sample effective haircut, percentage points

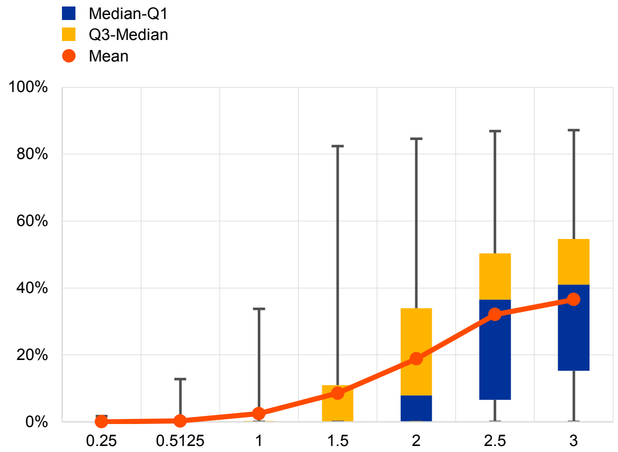


Source: authors calculations.

Chart 14.9

TLA haircut levels – distribution quantile analysis

Average sample effective haircut, percentage points



Source: authors calculations.

3 Systemic model modules

Modular model extensions are key to this top-down stress test set-up, as they provide the essential systemic flavour to the results obtained in the bank-specific analysis. These modular components mainly target model contagion or second-round effects and commonly interface with the granular information repository of the basic framework in a more contextual manner. The lender of last resort modelling is also essential from a policy perspective, while the two-way bridge between solvency and liquidity is needed to capture the full system dynamics under stress.

3.1 Explicit modelling of the lender of last resort

The role of the lender of last resort in a liquidity stress test exercise is an important parameter since it controls the amount of funding shortfall that can be provided by the competent central bank to the market as a backstop to a liquidity shortage.

While, until recently, the existing framework only allowed for stylised approaches to the modelling of the lender of last resort backstop, the highly granular information that is used in the basic model on encumbrance levels for collateral eligible for central bank funding enhances the ability of the framework to simulate various lender of last resort policy reactions. Some of the policy reactions that can be considered include the use of the existing/standard eligible securities buffer, the extension of the existing buffer to monetary policy operations or the APP program, the extension of the scope of eligible assets to accommodate the need for a more relaxed funding policy, and the adjustment of applicable haircuts to appropriate new levels to boost market confidence.

Since the presence of the lender of last resort acts as an initial buffer for the accommodation of banks' existing funding needs under severe funding stress, any residual (non-eligible) unencumbered TLA may be assumed to be directed to the interbank market for secured lending or sold to the market (fire sales component). Therefore, explicit modelling of a specific lender of last resort policy reaction (neutral or more accommodative) would be needed in order to properly define the magnitude of the contagion effects of the asset price transmission channel.

3.2 Fire sale effects

The framework allows for the evaluation of banks' pecking order policies, i.e. the order in which a bank utilises its available unencumbered TLA under liquidity stress. By assessing all banks and their reactions under a common exogenous funding stress, it is possible to evaluate whether each bank can withstand the shock by using its available TLA in the secured interbank market (in the form of collateralised repo transactions) or whether fire sales are to be triggered. In this context, a more pragmatic estimation of the envisaged volumes linked to fire sales and the potential supply of collateral for the secured interbank market can be considered.

Fire sale contagion is modelled by an increasing asset haircut on the basis of the higher proportion of assets of each type (commonality factor) that account for fire sales across the entire system (all banks). The model uses this commonality factor and an exogenous elasticity value for each asset class to adjust the projected market shock upwards. A similar approach can be followed for estimating the projected haircut of the repo market for each asset class, i.e. increased haircuts for an increased supply of assets for repo operations.[125]

Banks' fire sales have an impact on the valuation of liquidated assets and would affect banks' capital for those assets recognised at mark-to-market in their balance sheets. Notably, the liquidation has a system-wide amplification effect, meaning that the price of the assets is a function of the total volume disposed of by banks on the market. Moreover, banks' tight regulatory constraints may induce further liquidation of assets to restore acceptable levels of capital adequacy ratios. Consequently, a liquidity spiral phenomenon can be observed, similar to the one described by Cifuentes et al. (2005) for banking books or Brunnermeier and Pedersen (2009) for trading portfolios.

The algorithm is implemented following Hałaj and Kok (2013) and Greenwood et al. (2015), using an exponential functional form of the relationship between the volume

[125] An iterative algorithm may be used to estimate the final market shocks and adjusted haircuts to account for asset price second-round effects.

and price of the underlying assets. The elasticities of the relationship are calibrated to the findings of Eser and Schwaab (2013), which state that the liquidation of sovereign bonds of €1 billion results in an impact on yield of approximately 10 basis points, but varying across EU countries.

3.3 Funding network contagion model

Assessing a bank's liquidity situation in isolation from the system of links between institutions can lead to an underestimation of liquidity risks. The topology of the interbank connections, i.e. who provides funding sources to whom, is relevant to the scale and magnitude of the funding shocks.

Recent studies incorporate network-based connections between banks in liquidity risk studies. For instance, Ferrara et al. (2016) study the potential cascade funding problem, stemming from failures to roll over short-term funding or repay obligations when they fall due, which adversely affects the cash inflows of counterparties. They use UK banks' reporting on liquidity buffers and expected cash-flows produced as part of their recovery and resolution planning. Calomiris et al. (2015) use banks' relative position in the interbank network to explain seasonality in banks' lending activities and, consequently, the liquidity risks.

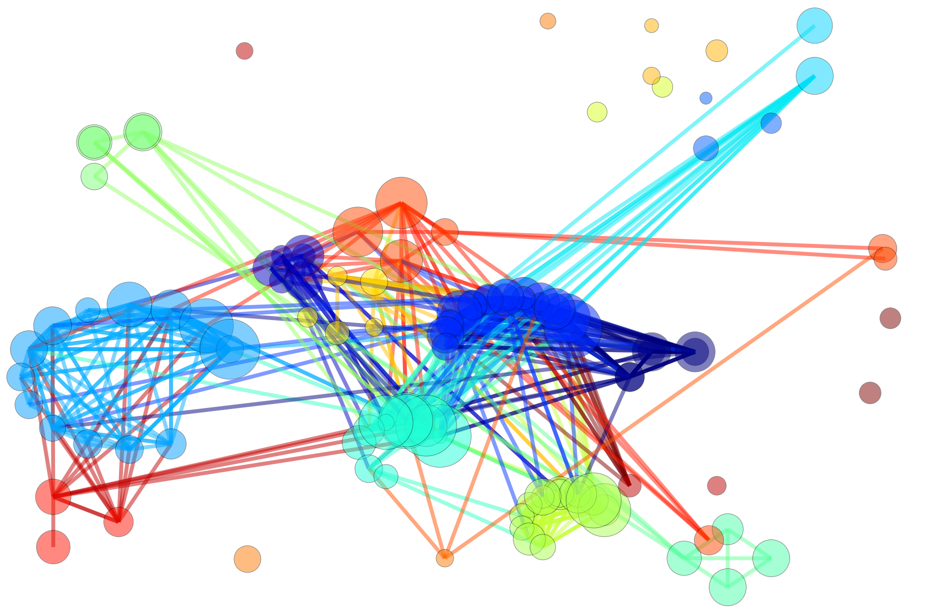
A random network approach, similar to the one used in solvency contagion analysis (see Chapter 12), is used here to incorporate into the liquidity stress test framework an additional stress element related to banks' reliance on interbank funding (secured or unsecured). It is assumed that banks experiencing an initial funding shock would hoard interbank liquidity by cutting interbank funding supply. Consequently, their counterparties would experience an additional funding shock that could further widen their funding gap and endanger the system.

As illustrated in Chart 14.10, the structure of interbank connections can be relatively heterogeneous. Some banks appear to be central in the market, i.e. they provide interbank funding to many counterparties. Since the structure of the market is relatively complex, simulations can only reveal the propagation and amplification channels.

Chart 14.10

Graphical representation of the (simulated) EUR unsecured interbank lending

A sample of the largest banks in the EU, colours represent countries



Source: authors calculations.
Notes: The probability map of Hałaj and Kok (2014) is used to set a prior on the likelihood of links in the random network generating algorithm; each node represents a bank. The size of the node is proportional to the logarithm of the sum of that bank's interbank exposures. The chart depicts the heterogeneity of interbank links and the complexity of potential contagion channels.

3.4 Liquidity and solvency link

Liquidity and solvency are usually treated separately. For instance, stress testing activities are split into solvency stress testing (e.g. EBA stress tests) and liquidity stress testing (e.g. Deutsche Bank, 2015).

In reality, a strong relationship between solvency and liquidity can be observed. Generating cash may only be possible in some circumstances with a high impact on profits and, consequently, adversely impacts the capital position. On the other hand, a shock to solvency that decreases the probability of the asset value exceeding the value of funding may trigger a run on the institution, weakening its cash position (or cash generation potential). One of the most prominent examples was the outbreak of the 2007-08 crisis, which was mainly driven by liquidity issues but translated into the bankruptcies of some of the largest market participants (e.g. Lehman Brothers and AIG). There is also a reverse relationship, in which solvency risk translates into funding risk. In 2010, as a second phase of the financial crisis, the poor capitalisation of banks was reflected in the funding cost spreads and aggravated by the solvency risk of some sovereigns.

The top-down stress test incorporates the solvency and liquidity links in the following ways:

- Impact on funding cost: if the drop in the capital ratio related to fire sales and interbank funding network effects is significant, banks may experience an increase in either the run-off rates of some wholesale funding sources or an increase in the funding spreads of the wholesale funding to be rolled over, since their actual or perceived solvency conditions may deteriorate. A stylised parameterisation of the additional spread requested for the rolled-over wholesale funding is used, defined as follows: 10 basis points for a capital ratio drop of 100 basis points and 25 basis points for a capital ratio drop exceeding 200 basis points.[126] Notably, not only banks that have experienced a significant drop in their capital ratios may be subject to higher funding spreads, but also banks that have similar business models to the directly affected banks. This step represents a potential indirect contagion effect. Banks' peers (those banks that have a similar balance sheet composition) are assumed to pay additional spreads on their maturing wholesale funding.[127]
- Cross-holding of debt channel: the initial funding shock can leave a capital footprint, if solvency impact is large enough to lead to the bankruptcy of banks once their capital falls below a required minimum. Consequently, cross-bank exposures are resolved and contagion spreads via interbank lending and the cross-holding of bank debt securities. Notably, the effects related to the cross-holding of bank debt might be rather limited since some empirical results (see Hüser et al., 2016) suggest that the exposures in this channel are relatively small.

3.5 Combined effects – simulation

The systemic amplification effects of funding shocks via fire sales, interbank linkages and funding conditions as a function of solvency and cross-holding of debt channels are integrated into a six-step framework to analyse the propagation of the funding shock across the system and to identify the key driving amplifiers, introduced by Hałaj (2016). This is one potential way of integrating some of the components of the liquidity stress test described above. The initial shock structure relates to the funding sources of banks (in practice to retail or wholesale deposits, asset-backed instruments, etc.). This may trigger steps (a) to (f) described below:

a. For shocks on the banking system side, banks verify whether they have sufficient eligible collateral of sufficient quality to enter into repurchase agreements. Should the redemptions affect asset managers, they are assumed to use cash first to meet the outflows. If banks possess enough eligible collateral, no further steps follow and the shock is contained within the high-quality counterbalancing capacity.

b. If the eligible asset buffer is insufficient for a given bank, it resorts to interbank assets. The bank hoards the additional short-term interbank lending in an attempt to

[126] The ongoing empirical work aims to establish a link between the funding costs and banks' solvency positions.

[127] The similarity is quantified in terms of a cosine ratio; two banks are peers if, and only if, the cosine between a vector created from the volumes of their asset and liability categories is close to 1.

cover the remaining gap resulting from the first step. Consequently, banks that funded themselves by deposits from another bank need to search for alternative sources. This is assumed to induce additional funding spread related to the search cost. The spread impacts banks' profit and loss and capital. Notably, the topology of a network of interbank exposures determines the direction in which the contagion spreads across the system.

c. The fire sale step is triggered if the verification fails for banks and there was not enough capacity in their interbank portfolios to generate liquidity to cover the initial funding shock. Banks liquidate less liquid assets. This has an impact on their valuation and would impact banks' capital for those assets recognised at mark-to-market in their balance sheets. Notably, the liquidation has a system-wide effect, meaning that the price of the assets is a function of the total volume disposed of by banks on the market.

d. Losses accumulated in steps (a)-(c) impact banks' capital ratios. If the drop in the capital ratio is significant, banks may experience an increase in funding spreads of the wholesale funding to be rolled over, since their actual or perceived solvency conditions may deteriorate. This mechanism is captured in this step.

e. It is not only banks that have experienced a significant drop in their capital ratios that may be subject to the elevated funding spreads, but also banks that have similar business models to the directly affected banks (peer group). Potential indirect contagion effects – an information channel – are modelled in this step. Banks' peers are assumed to pay additional spreads on their maturing wholesale funding.

f. Some longer-term effects of the initial funding shock that leave a capital footprint are gauged in this step. All losses aggregated from steps (a)-(e) undermine banks' solvency. In some cases, this may lead to defaults once the capital falls below a required minimum. Consequently, cross-bank exposures are resolved and contagion spreads via interbank lending and the cross-holding of bank debt securities.

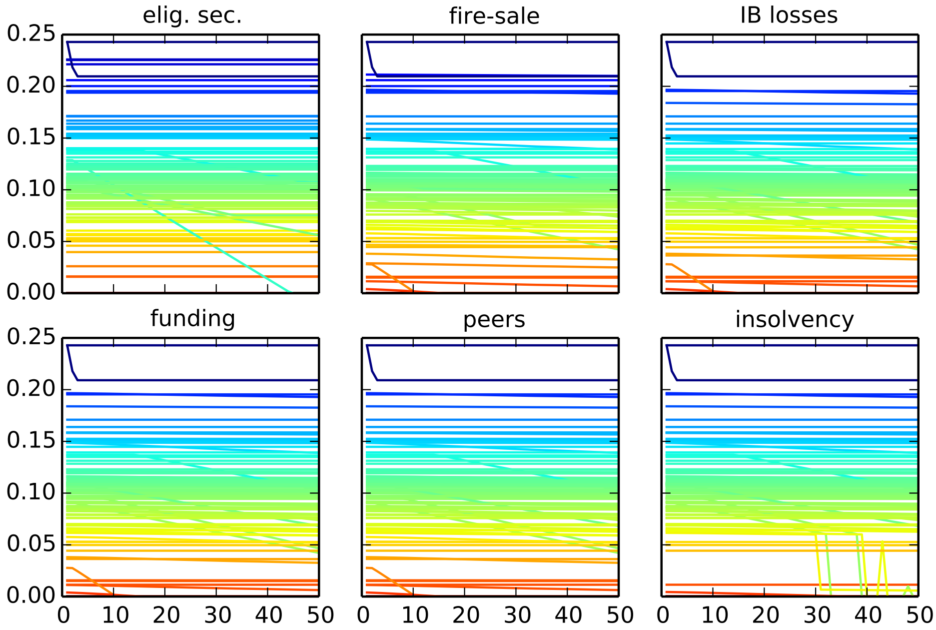
Many of the parameters of the model are set in an ad hoc fashion and the calibration work is ongoing. For instance, the thresholds of significant reduction in the capital ratios that would imply a higher funding cost of the rolled-over volumes, as well as the peer groups, are counterfactual.

The functioning of the integrated framework is illustrated for a specific type of scenario of a funding shock to the long-term corporate funding and covered bond outflow affecting a given group of banks. A range of outflow parameters from 1% to an extreme case of 50% is applied. Outcomes of the simulations are shown in Chart 14.11. Each line represents the capital ratio of a given bank as a function of the magnitude of the shock (realised as a percentage outflow of the initial stock of funding). A large majority of banks is not significantly affected by the shocks. Their capital stays at the initial level, independent of the size of the shock (or falls slightly due to a common revaluation caused by fire sales). However, there is a subset of banks which react quite strongly: their capitalisation deteriorates steadily as the magnitude of the shock increases. An interesting nonlinearity of the responses can be observed in the last step of the algorithm. There is a threshold level of the shock (above 30%, but varying for banks) that drives a few banks into negative capitalisation. This is the result of some substantial cross-holdings of bank bonds implied by the applied random matching algorithm.

Chart 14.11

Sequence of simulations: outflow of funding related to term corporate deposits and covered bond.

The boxes correspond to steps (a)-(f) of the six-step model



Source: authors calculations.
Notes: x-axis – outflow (percentage of initial stock in a bank); y-axis – capital ratio.

The spreading of a liquidity shock can be contained within national borders or have a cross-border dimension. In the latter case, the effectiveness of any macroprudential policy that attempts to reduce the consequences is more complicated since it depends on the coordination between jurisdictions. A stylised simulation has been carried out to assess the potential magnitude of the cross-border impact of a 20% funding outflow through the liquidity and solvency link, amplified by the fire sales and interbank funding network. The simulation has been conducted for each funding class by randomly selecting a sample of banks. A number of banks (*n*) was drawn from the Poisson distribution and then a sample of *n* banks was drawn from the uniform distribution. By assumption, the mean of the distribution is equal to 2. The results are aggregated per country.

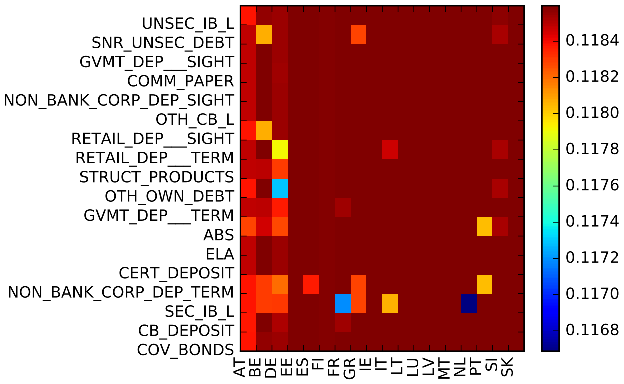
The effects measured by capital reduction are presented in Figures 14.12 and 14.13. A set of simulations was conducted to assess systemic vulnerability to a shock to a given category of funding sources in a given country. For each pair of category-county shock, an aggregate impact on banks' solvency in the whole system can be computed. In this way, a heatmap of vulnerabilities can be constructed.

Outcomes are presented for one particular calibration of the shock, common in magnitude across the pairs, to make the outcomes comparable, i.e. a 20% funding outflow. In the worst cases of the category-country pairs affected by the initial shock, the overall impact is of a magnitude of 20 basis points. Capital is unaffected in 70% of pairs. In general, the cross-border effects are rather limited (a reduction of only a few basis points in the average capital ratio of banks in a given country). The magnitude of the cross-border effects correlates with the domestic impact, i.e. the larger the domestic vulnerability to the shock, the larger the cross-border spillover.

Chart 14.12

Heatmap of the shock transmission (20% outflow) aggregated by country

(basis points)

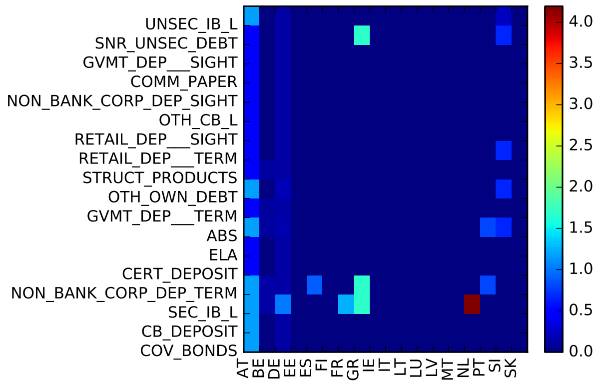


Source: authors calculations.
Note: Colours encode the average capital ratio in the sample of analysed banks after a funding shock to a given liability class hits banks in a given country.

Chart 14.13

Heatmap of the cross-border spillovers of a funding shock (20% outflow) aggregated by country

(basis points)



Source: authors calculations.
Note: Colours encode the average capital ratio in the sample of analysed banks after a funding shock to a given liability class hits banks in a given country.

4 Conclusion

This chapter presented the basic components of the top-down liquidity stress testing models. While the work on liquidity models is still ongoing, it is evident that the targeted utilisation of a wide variety of data sources available to the ECB could allow a robust framework for monitoring systemic vulnerability for macroprudential purposes to be established.

Since data quality is also expected to improve gradually,[128] the model framework could be updated on a quarterly basis and provide comparable regular metrics for financial stability purposes.

Introducing appropriate monitoring metrics (such as the DLSI) fully targets such a perspective, since it can be used to encompass the available information on the liquidity stress condition of individual banks, aggregate sectors and clusters, or the market as a whole. This would, to some extent, standardise the framework for monitoring and identifying liquidity-related financial stability risks and would largely facilitate analysis across market segments and over time.

128 Reporting requirements based on the Implementing Technical Standards on Asset Encumbrance have recently been brought into force.

Further integration of the systemic models into the basic bank-by-bank framework is essential for assessing the systemic aspects of liquidity stress scenarios, since contagion effects might prove to be important for a significant proportion of the scenarios considered. Systemic model modules are assessed on the basis of the importance of their relative impact, and a uniform and consistent approach as regards the necessary assumptions and prioritisation of second-round effects is being examined.

Additional modular extensions are being considered, mainly on the basis of the availability of data of a sufficient quality. Accordingly, the priority is to develop a module capturing interlinkages with shadow banks in a realistic way and a module targeting the measurement and calibration of the solvency impact of liquidity stresses. In parallel, equally important work on improving the accurate calibration of liquidity shocks on the basis of both past/historical experience and more recent market developments is also one of the main areas of focus.

Finally, another priority would be to exploring further the concept of using agent-based models in replicating properties of real economic systems which emerge from interaction between heterogeneous agents. Contagion effects and the emergence of market failures based on the interactions of agents within an agent-based modelling framework and using a set of simple behavioural bias rules suggests that this type of tool might be efficiently used for the modelling of similar externalities

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5 Annex

Table 14.A.1
Haircuts on sovereign exposures by rating class, maturity and scenario

	0M – 3M	3M – 1Y	1Y – 2Y	2Y – 3Y	3Y – 5Y	5Y - 10Y	10Y +	Total – mild	Total – adverse	Total – severely adverse
AAA	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
AA+	0.09%	0.09%	0.24%	0.32%	0.43%	0.57%	0.66%	0.25%	0.30%	0.38%
AA	0.19%	0.19%	0.48%	0.64%	0.86%	1.14%	1.31%	0.50%	0.60%	0.75%
AA-	0.38%	0.38%	0.95%	1.29%	1.71%	2.29%	2.63%	1.00%	1.20%	1.50%
A+	0.75%	0.75%	1.90%	2.58%	3.42%	4.58%	5.25%	2.00%	2.40%	3.00%
A	1.13%	1.13%	2.85%	3.86%	5.14%	6.86%	7.88%	3.00%	3.60%	4.50%
A-	1.50%	1.50%	3.80%	5.15%	6.85%	9.15%	10.50%	4.00%	4.80%	6.00%
BBB+	1.88%	1.88%	4.75%	6.44%	8.56%	11.44%	13.13%	5.00%	6.00%	7.50%
BBB	2.25%	2.25%	5.71%	7.73%	10.27%	13.73%	15.75%	6.00%	7.20%	9.00%
BBB-	2.63%	2.63%	6.66%	9.01%	11.99%	16.02%	18.38%	7.00%	8.40%	10.50%
BB+	3.00%	3.00%	7.61%	10.30%	13.70%	18.30%	21.00%	8.00%	9.60%	12.00%
BB	3.38%	3.38%	8.56%	11.59%	15.41%	20.59%	23.63%	9.00%	10.80%	13.50%
BB-	3.75%	3.75%	9.51%	12.88%	17.12%	22.88%	26.25%	10.00%	12.00%	15.00%
B+	4.69%	4.69%	11.89%	16.10%	21.40%	28.60%	32.81%	12.50%	15.00%	18.75%
B	5.63%	5.63%	14.26%	19.32%	25.68%	34.32%	39.38%	15.00%	18.00%	22.50%
B-	7.50%	7.50%	19.02%	25.76%	34.24%	45.76%	52.50%	20.00%	24.00%	30.00%
CCC+	9.38%	9.38%	23.77%	32.19%	42.81%	57.20%	65.63%	25.00%	30.00%	37.50%
CCC	11.25%	11.25%	28.53%	38.63%	51.37%	68.64%	78.75%	30.00%	36.00%	45.00%
AF	5.63%	5.63%	14.26%	19.32%	25.68%	34.32%	39.38%	15.00%	18.00%	22.50%
LA	3.75%	3.75%	9.51%	12.88%	17.12%	22.88%	26.25%	10.00%	12.00%	15.00%
ME	5.63%	5.63%	14.26%	19.32%	25.68%	34.32%	39.38%	15.00%	18.00%	22.50%
OAE EEA	0.56%	0.56%	1.43%	1.93%	2.57%	3.43%	3.94%	1.50%	1.80%	2.25%
OCEEC	3.75%	3.75%	9.51%	12.88%	17.12%	22.88%	26.25%	10.00%	12.00%	15.00%

Notes: Actual haircuts shown are based on the mild scenario assumption, while adverse and severely adverse scenario haircuts may be calculated using the mild base multiplied by the proposed scalar (1.2 or 1.5) and applying the logarithmic interpolation deriving a haircut for different tenors. Haircuts are calculated based on several sources, including authors calculations, EBA stress test exercises and outside references and case studies (like Lehman Brother's crisis).

Chapter 15 The Integrated Dynamic Household Balance Sheet (IDHBS) Model of the euro area household sector

By Marco Gross and Javier Población[129]

This chapter addresses the need for models that capture the dynamics of the household sector, and specifically its demand for bank credit, as well as the risks associated with that for the household sector itself and the economy as a whole. The household loan mortgage segment is among the most material in terms of banks' total loan exposures. Moreover, debt-financed house purchase activities by the private sector lie at the root of endogenous, self-evolving business and financial cycles. In a macroprudential policy context, the household sector also deserves special attention as it is the target of measures such as loan-to-value (LTV), debt-to-income (DTI) and debt-service-to-income (DSTI) ratio caps. All these ratio caps affect households' effective demand for credit from banks and thereby the economy's aggregate debt and ultimately financial and business cycle dynamics.

Against this background, this chapter presents an integrated micro-macro model framework that uses household survey data for 15 EU countries covered by the Household Finance and Consumption Survey (HFCS). For assessing the effects of borrower-based measures, such micro data are key because they can help capture distributional effects much more than aggregate (average) statistics. The model can be used for stress testing households and thereafter banks. It also enables to assess the impact and relevance of borrower-based macroprudential instruments, i.e. the LTV, DTI and DSTI ratio caps, and therefore to assess their relative effectiveness under various scenarios and assumptions.

1 Introduction

The purpose of this chapter is to present the first version of the Integrated Dynamic Household Balance Sheet (IDHBS) model for the euro area household sector. The IDHBS model is composed of a number of modules. One major component of the model suite is based on the balance sheets of 60,000+ individual households (comprising 150,000+ household members) from a subset of 15 European countries contained in the HFCS.

The model is inherently "micro" in nature as the balance sheet structure and profit and loss variables are modelled at the household and household-member levels.

[129] Based on Gross and Población (2017).

Alongside the micro component of the model, a macro-financial model component is part of the tool suite – a Global Vector Autoregressive (GVAR) model, covering ten core macro-financial variables for the 28 EU countries.

The GVAR model serves as a stochastic simulation engine that generates a large number of consistent multivariate, multi-country forward paths for variables. These variables are used to steer the household-member or household level parameters which determine the value of their real and financial assets, as well as their income and expense streams, to obtain measures of probabilities of default, loss given default, and loss rates at the household and household-sector aggregate levels.

An additional component of the model envisages a link between the household sector risk parameters (aggregated from household to country level) and banks' balance sheets and profits and losses (P&Ls). The mortgage portfolios of the SSM sample of banks are taken as a starting point, including their size and risk parameters. The IDHBS model can be used to estimate the differential impact of LTV or DSTI ratio caps on the capital (CET1) position of the banks.

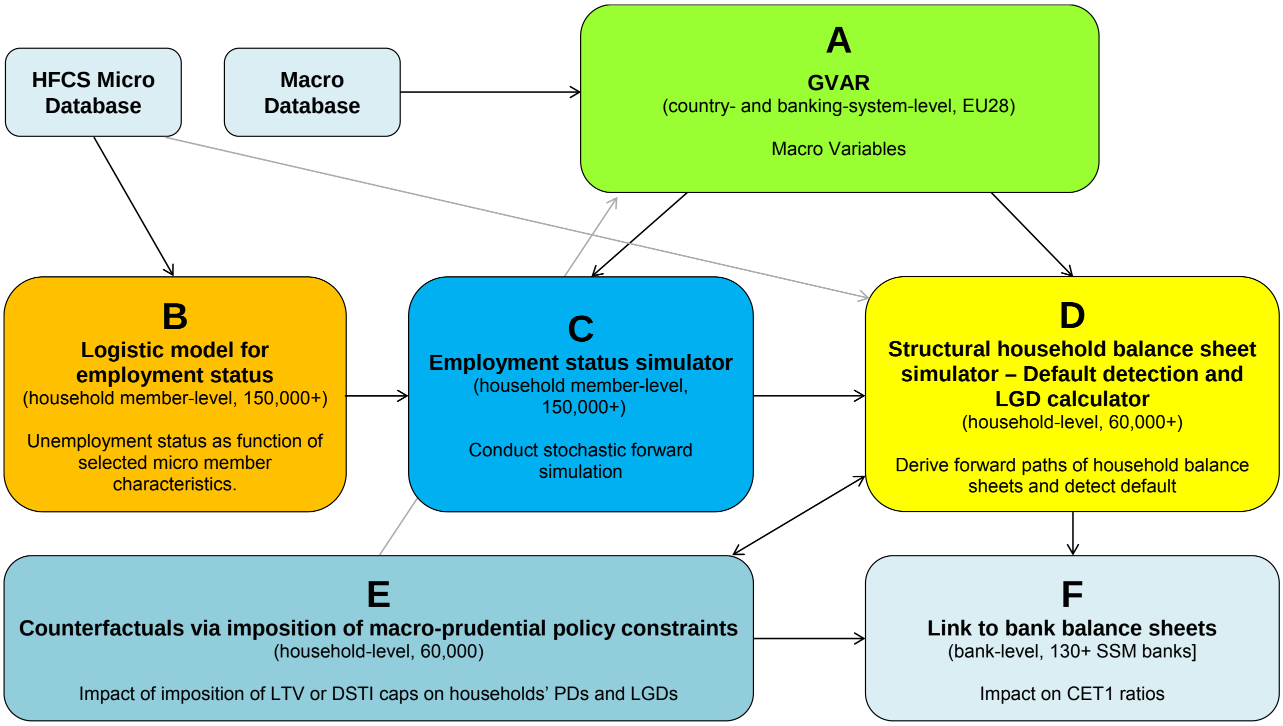
Specifically, the imposition of LTV or DSTI ratio caps will be assessed, as a first step, with regard to their primary impact through the exclusion from the mortgage market of households whose LTV/DSTI ratios are above an assumed threshold. At this point, the drop in loan demand which would have (retrospectively) resulted from the imposition of some LTV or DSTI cap can be quantified. Next, the model can be used to assess the secondary impact of LTV/DSTI ratio caps through macro-feedbacks which would arise as a result of the reduced mortgage loan demand the moment that such policy measures are introduced.

Section 2 presents the data underlying the model framework and the various model components. Section 3 presents some illustrate simulation results from the model. Section 4 concludes.

2 Data and model structure

Chart 15.1 summarises the structure of the model. It consists of two database inputs and six core modules (labelled A-F).

Chart 15.1
Model structure



2.1 HFCS Micro database

The model is built on a unique micro survey database – the Eurosystem HFCS – which is a decentralised survey of the Eurosystem in which all participating institutions (national central banks and, in a few countries, national statistical institutes) conduct their own wealth survey. The HFCS then provides the Eurosystem with harmonised micro-level data on euro area households' finances and consumption.

The HFCS survey consists of questions referring to the household as a whole (answered only by a single person: the main respondent) as well as those targeted to individual household members (basic demographic information collected for all household members and a personal questionnaire answered by each household member over 16). The survey part covering household-level questions encompasses: real assets and their financing; liabilities and credit constraints; private businesses and financial assets; inter-generational transfers and gifts, and consumption/savings. Questions to individuals cover the following areas: employment, future pension entitlements and labour-related income (other income sources being covered at household level). The distinction between household member and household level variables is important and will become clearer once the various modules of the IDHBS model are described below.

2.2 Macro database

The macro database covers ten variables for 28 EU countries, i.e. 280 time series, with a quarterly frequency over the period from the first quarter of 1995 to the fourth quarter of 2014. The variables are the input to the macro model component of the IDHBS model and include the following: unemployment rates, long-term interest rates (ten-year benchmark government bond yields), stock price indices, nominal compensation per employee, residential property price indices, nominal GDP, GDP deflator, and short-term interest rates (three-month money market interest rates).

Along with the macro/economy-level variables, two banking system variables are included: nominal loan growth and aggregate loan interest rates. Moreover, an additional significant portion of the macro database contains the trade and domestic and cross-border credit series, which are an input to the model structure for the calibration of the weights that are needed to set up the GVAR structure.

2.3 Module A: the GVAR

The GVAR model serves to capture all domestic and cross-border dependencies of the aforementioned ten variables at country and banking-system level (EU28). Based on the estimated model (comprising 280 equations), a stochastic forward simulation is conducted to generate a large number of consistent multivariate, multi-country forward paths with a horizon up to 16 quarters for the ten variables. The paths are consistent in the sense that historical dependencies between variables within and across countries are reflected in the simulated forward paths.

2.4 Module B: logistic model for employment status

The purpose of the module is – by means of the logistic models for all countries – to endogenise the employment status of individual household members and, more specifically, to use the logistic model engine in the subsequent Module C to simulate a distribution of outcomes for the employment status of individual household members while aligning them with aggregate unemployment rates.

The logistic model for the employment status operates at household member level. The household member employment status is the dependent variable. Retirees and students are excluded and only employed, self-employed and unemployed household members are considered. No distinction is made between employed and self-employed in the model, i.e. the two groups are pooled, thus the model is a binomial logistic model for each country that distinguishes between being employed and unemployed for each household member.

The explanatory variables include age, gender, marital status, highest level of education completed, and whether or not the household member has a public pension. All intercept and slope coefficients of the logistic model are country-specific, i.e. the logistic model is effectively estimated country by country.

2.5 Module C: employment status simulator

This module receives two inputs: the logistic model estimates from Module B as well as the simulated forward paths from Module A (GVAR) for the aggregate unemployment rates at country level. The role of Module C is to simulate the employment status of household members from the logistic model – given the fixed household member characteristics such as age, gender, etc. – while adjusting the intercept term of the logistic model (per country) to match the aggregate unemployment rate forward paths derived from the GVAR. This intercept adjustment is done for all (1 million) joint multi-country forward paths from the GVAR sequentially.

An important technical feature embedded in Module C is that it takes an aggregate duration of unemployment parameter (country-specific) into account while conducting the forward simulation along the 16-quarter horizon.[130] The error term of the logistic model is assigned a persistence parameter which is set such that the aggregate duration of unemployment is matched (specific to each country).

If the persistence in the error term were not introduced, the prevalence of employment or unemployment status for the individual household members would be random along the scenario horizon. Household members would as a result too often switch back and forth between being employed and unemployed, which is not realistic and would distort the subsequent assessment of how often a household's liquid assets are insufficient to service its outstanding debt. Technically, the error persistence/duration matching could, in principle, be replaced by a time series model on employment status migration if such data were available. The HFCS database, however, offers only one cross-sectional dataset for a point in time, i.e. the time series dimension is missing. The quasi-time series dimension was therefore introduced via error persistence to match the aggregate duration of unemployment.

2.6 Module D: structural household balance-sheet simulator, default detection and LGD calculator

The structural household balance sheet module operates at household level, i.e. the household member information from Module C (employment status simulator) is combined by assigning household members to their households. It is therefore the combined household balance sheet that serves as a basis for the measurement of default probabilities and LGDs, while the P&Ls of the household – in particular the income part of it – is driven by the household members, specifically by their employment income or unemployment benefit respectively. Table 15.1 shows a schematic picture of the structure of the household balance sheet that the model structure is built around.

[130] Aggregate duration of unemployment estimates can be found in the OECD's data warehouse.

Table 15.1
Household balance sheet

Assets		Debt and equity	
AR	House/land (H)	LM	Mortgage debt
		LC	Consumer credit
	Other real valuables (VR)		
AF	Cash		
	Sight deposits (DSI)		
	Term deposits (DTE)		
	Bonds (B)	E	Equity
	Stocks (S)		
	Other financial valuables (VF)		

Assets are grouped into real (A^R) and financial (A^F). The market value of houses and land is subsumed into the variable H. The residual of all other real tangible assets is denoted as V^R. Financial assets include cash, sight and term deposits, holdings of sovereign, corporate or other bonds (B), shares in listed companies (S) as well as, again, a residual category of items (V^F), including, for instance, savings that have accumulated in pension funds, insurance funds, or the like.

On the liability side, the household may face an amount of debt (L) which can be outstanding in the form of a mortgage (L^M) or other debt, which can be referred to as consumer credit (L^C), for cars, other household equipment, etc. Total assets are the sum of real and financial assets (A=A^R+A^F) and the gap between total assets and total outstanding debt, called equity (E=A-L). Importantly, all information about the balance-sheet size and structure defined up to here relates to the household as a whole, i.e. the corresponding data from the HFCS is extracted from the household-level part of the database.

The P&L side also involves a number of variables that need to be defined. First, gross income from self-employed or employed work is defined as INC^G. The net salary after tax is denoted as SAL^N, which equals the gross salary less an amount of income tax as a function of a tax rate r, that is, $SAL^N = SAL^N \times (1 - r)$. This variable is defined and measured at household member level and is positive only for employed members. If a household member is unemployed, he/she shall receive an unemployment benefit (U^N).

The change in the market value of liquid assets such as bonds and stocks is denoted as RET^B and RET^S respectively for bonds and stocks. Even though households would not sell bonds or stocks during the forward simulation, the value change in these assets is assumed to be immediately recognised through the households' P&Ls.[131]

The expense components relate to outstanding debt, namely a periodic debt repayment denoted by EXP^M for mortgages and EXP^C for consumer credit ($\mathrm{EXP} = EXP^M + EXP^C$). In addition to debt payments, households face a cost of living (LIV), which, if a household member is employed, is defined relative to the periodic net salary, i.e. $LIV^e = I^e \times SAL^N$, or if he/she is unemployed, relative to the net unemployment benefit, i.e. $LIV^e = I^e \times SAL^N$.

With all variable definitions at hand, one can now define the way the household balance-sheet stocks move forward in time. The focus lies on the combined value of liquid assets, i.e. cash and deposits, as well as bond and stock holdings. Liquid

[131] The value of bond and stock holdings is initially extracted from the household-member level part of the database but is then pooled at the household level.

assets evolve over time depending on the employment status of each household member as follows:

$$\Delta \text{Liquid Assets}_t = \Delta \text{B}_t + \Delta \text{S}_t - \min(\text{L}_t, EXP_t) + \begin{cases} \sum_{n1=1}^{N} INC_{n1,t}^{G}(1 - \text{r}_t)(1 - \text{l}^e) \text{ if employed} \\ \sum_{n2=1}^{N} U_{n2,t}^{N}(1 - l^u) \text{ if unemployed} \end{cases}$$

Where ΔB_t and ΔS_t represent the change in the values of bonds and stocks at time *t*, L_t is the outstanding loan amount and EXP_t is the periodic debt repayment. Finally, *INC* and *U* represent the salary or the unemployment benefits depending on the employment status. From these amounts, the cost of living (*l*) and taxes (*r*) should be subtracted.

If liquid assets become negative in any period along the simulation horizon t=1…T, the household is assigned a default flag. Once a household receives this flag, this household and its members' income and expenses are not further simulated in time, i.e. it is not allowed to potentially recover by assumption.[132]

Along with the default indicator that is tracked for each household, an LGD is computed continuously. Provided that there is a default, two possibilities are considered: the bank confiscates the house in the near future or the household recovers and continues repaying the mortgage loan.

$$\text{LGD} = \text{P}^C \times \text{LGD}^C + (1 - \text{P}^C) \times \text{LGD}^{NC}$$

with P^C being the probability of confiscation and LGD^C and LGD^{NC} being the LGD under the two scenarios of confiscation or no confiscation. The probability of confiscation and the LGD under the recovery scenario are defined exogenously whereas the LGD under the confiscation scenario evolves dynamically over the simulation horizon as a function of house prices.

The discount rate is defined as follows:

$$\text{Discount} = \frac{1}{(1 + LTN)^{\text{Confiscation\_time}}}$$

where LTN is the long-term interest rate at the time of confiscation.

The value of the house at the time of confiscation ($V^{Tconfisc}$) is aligned with the house price change (from the GVAR) between the time of default ($\text{T}_{\text{default}}$) and the time of confiscation ($\text{T}_{\text{confisc}}$), that is:

$$\text{V}^{Tconfisc} = e^{(\ln(\text{V}^{Tdefault}) + \ln(\text{HP}^{Tconfisc}/\text{HP}^{Tdefault}))}$$

where HP is the country-level house price variable from the GVAR.

The LGD under the confiscation scenario is:

[132] This conservative assumption is made for the sake of simplicity. It does not affect the results significantly since recoveries imply a lower LGD, which has been taken into account in the LGD corresponding to the "no confiscation" scenario.

$$\mathrm{LGD}^{C} = 1 - \frac{\mathrm{Min}\,[\mathrm{V}^{Tconfisc} + V^{R}, L^{M} * (1 + \mathrm{Ad\_Cost})]}{L^{M}} * \mathrm{Discount}$$

where “Ad_Cost” are the administrative costs.

The macro (i.e. country-level) variables from the GVAR engine drive the household and household member-level variables. The compensation per employee variable from the GVAR steer the income path for employed household members. Log percentage changes of income from the GVAR are attached to the household members’ quarterly income starting points. Stock prices from the GVAR are used to re-value the stock holdings of a household (pooled from household members). Log percentage changes of equity prices from the GVAR are attached to the household level value of stocks at the survey date. Long-term interest rates (ten-year benchmark government bond yields) from the GVAR are determine the value of bond holdings of the households. Absolute changes of long-term rates, quarter-on-quarter, are used to re-compute the market value of the bonds. This variable also serves as input to the LGD formula (as a discount factor). Moreover, apart from these inputs that flow directly from Module A (GVAR) to the current Module D, there is the indirect connection via Module C, the employment status simulator. Importantly, to recap, the forward paths generated in Module A feed through Module C to D and directly to D in a consistent manner. This is essential to properly capture all the dependencies between the variables involved in the macro and micro parts of the model.

2.7 Module E: counterfactual macroprudential policy simulations

The counterfactual policy simulator currently operates on LTV ratio caps and DSTI ratio caps. The module takes the simulated default and LGD forward paths from Module D as input and, as a first step, excludes the households whose LTV/DSTI ratios are above a self-set threshold level. Then the PD/LGD/LR aggregator is re-run on the reduced population to obtain an impact estimate for the policy measure.

The HFCS contains the information on when a mortgage loan was taken out. For the imposition of the initial LTV constraint, a reference period (one or multiple years) can be chosen in the model; only the households whose mortgages were granted during that period are then excluded. The DSTI constraints on the other hand are defined with respect to the current DSTI, i.e. the level of current periodic debt payments relative to current periodic gross income.

An additional simulation mode aims to account for the macro-feedback effects that may arise from imposing LTV/DSTI constraints as a result of reduced loan volume growth, as a part of the household population is prevented from obtaining a mortgage loan. This policy-induced negative credit demand shock is calibrated based on the HFCS data, specifically as the portion of household mortgages that are being excluded, given the LTV ratio cap relative to the total volume of mortgages granted in the reference period. The credit demand shock is then taken as input to Module A (GVAR) for a given country to simulate the responses of all model variables (sign constraints are involved to identify the impulse responses as credit demand shocks).

The GVAR model structure is also useful to gauge – in this particular context of country-specific LTV/DSTI ratio caps –the potential cross-border spill-over effects through the trade channel at country level, or financial market spill-overs which may cause the valuation of stock and bond holdings of households to react beyond the national borders where a policy measure was introduced.

The direct impact on aggregate LGDs would be rather mechanic, namely negative, as lower aggregate LTV ratios imply that more collateral is available to secure household loans and hence imply lower LGDs. The combined effect (including second-round effects) on loss rates from a credit provider perspective is likely to be negative (i.e. loss rates fall) considering first-round effects only.

Second-round effects can be split into short-term and medium-term effects. One sort of short-term effect (which can be assessed based on the current version of the IDHBS model) may arise as a result of reduced credit demand, in response to which economic activity may drop, partly due to less construction. GDP would drop and unemployment rates might rise which would imply some counteracting upward pressure on PDs. Downward pressure on house prices or at least less intense positive growth (desired by the policy) would let LGDs rise as the expected value of housing collateral would fall.

Other short-to medium term second-round effects (which cannot yet be addressed with the current version of the model) may arise as a result of reduced PDs and LGDs, and, consequently, loss rates in banks. Banks that face lower loan losses can employ their funds more productively and invest in profitable projects or create loans, which would imply a positive contribution to aggregate economic activity. Moreover, households with more stable balance sheets, being less inclined to take on sizeable (oversized) debt amounts, would contribute to developing a more sustainable forward path for households, with their PDs being lower in the long run.

Overall, considering the various channels and their implied signs and sizes of potentially counteracting effects on PDs and LGDs, the net effects of the first and second-round effects on the risk parameters would need to be assessed, as a function of the initial LTV/DSTI thresholds, and country by country, to account for differences in the sensitivities of macro and financial variables to credit demand shocks.

2.8 Module F: link to bank balance sheets

The final element in the module chain is the one that links the PD/LGD/LR paths of the household segments for all countries to the banks' balance sheets. The SSM sample of banks serves as a basis for the calibration of the module at the moment. The banks' mortgage portfolios in their home countries, as well as possibly their cross-border exposures through subsidiaries, are assigned the counterfactual (either purely scenario-conditional or policy-conditional as well) risk parameters from Modules D/E to assess the Common Equity Tier 1 (CET1) capital reaction.

The assessment is arguably partial as only the implied losses and foregone interest income for the mortgage loan portfolios of the banks are under scrutiny – either conditional or not conditional on the policy measures. All other loan portfolio segments as well as mark-to-market valuation effects for the banks' trading portfolios in response to stock and bond price changes are currently disregarded. It would – in terms of the model structure – be quite possible to account for these and other effects, although they are deliberately not accounted for to separate out the effects on banks' capital positions, through the income and loss generated from their mortgage portfolios only, when either considering or excluding the imposition of LTV/DSTI ratio caps.

3 Illustrative simulation results

Empirical results are presented in this section for four countries[133]: Austria, Belgium, Germany and Portugal. Table 15.2 reports the number of households and household members for the four countries.

Table 15.2

Micro data, household and household-member count

	Total population in survey			Population for which mortgage outstanding and initial LTV available		
	Households (HHs)	Household members (HMs)	HM/HH	Households (HHs)	Household members (HMs)	HM/HH
Austria	2,380	5,014	2.1	384	1,127	2.9
Belgium	2,327	5,516	2.4	655	2,070	3.2
Germany	3,565	8,134	2.3	812	2,332	2.9
Portugal	4,404	11,126	2.5	1,016	3,082	3.0
Total	**12,676**	**29,790**	**2.4**	**2,867**	**8,611**	**3.0**

The IDHBS model is first run under a baseline mode with a one-year horizon. The effective simulation horizon for Module A (GVAR) is set to three years because the liquidation time for housing collateral is assumed to be eight quarters. Thus, for households that happen to default at the end of the first year, an LGD can be computed with the additional eight-quarter horizon, for which, in particular, the simulated house price path is required. The output from the model (Module D) is a PD and LGD baseline estimate for each household that has mortgage debt outstanding. Moreover, at this point the model delivers a probability of each household member being employed (from Module B).

[133] Results are shown for four countries by way of illustration. More results can be found in Gross and Población (2017).

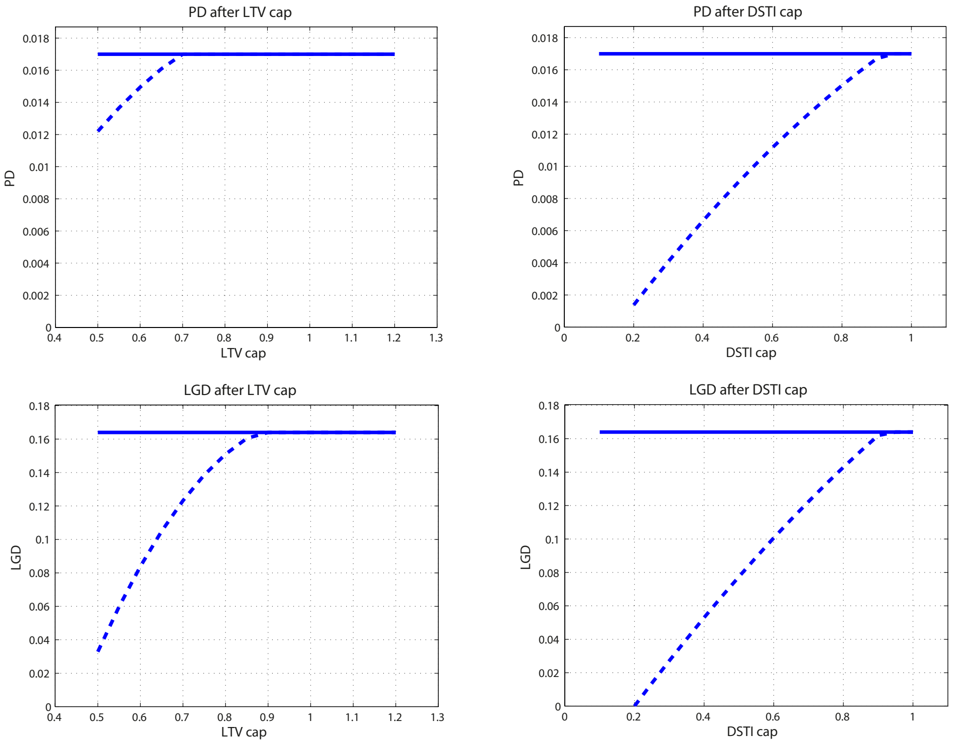
3.1 LTV versus DSTI caps

A first question to address is by how much LTV caps and DSTI caps are able to reduce household PDs and LGDs. A grid is defined for the LTV cap which spans the range from 0.5 to 1.2, and for the DSTI cap a grid that ranges from 0.1 to 1. The caps are imposed to compute the implied EAD-weighted PDs and LGDs for a country after the portion of the population whose initial LTV or DSTI stand above the assumed caps is excluded. Chart 15.2 presents the results for two countries.[134]

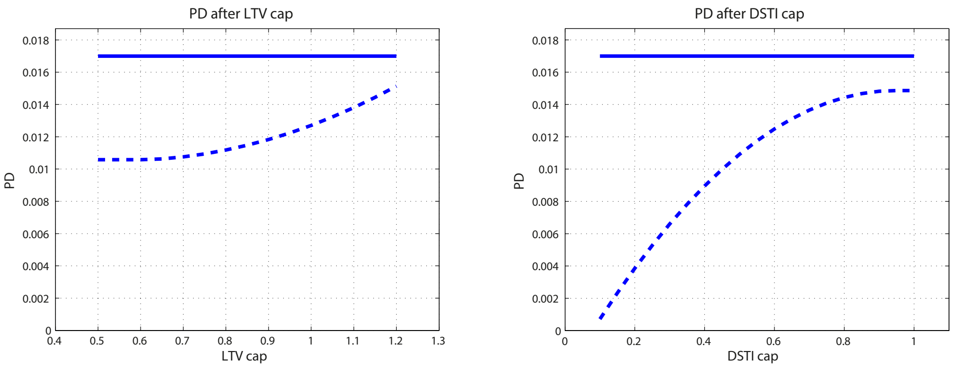
Chart 15.2

LTV versus DSTI impact assessment

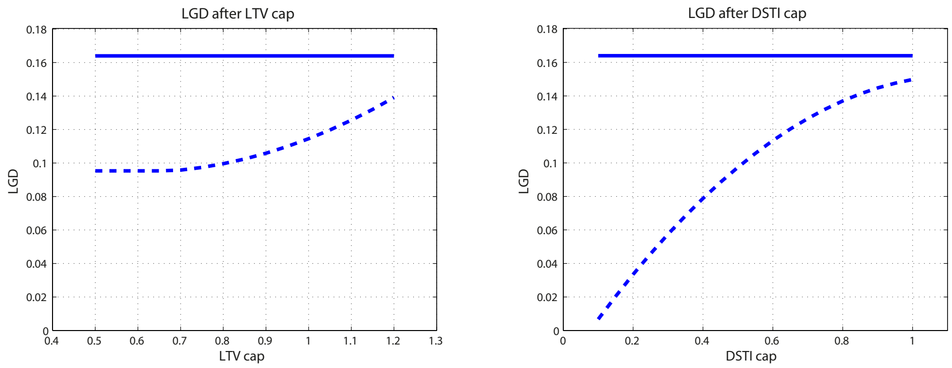
Austria



Belgium



[134] Results are shown for two countries by way of illustration. More results for an extended set of countries can be found in Gross and Población (2017).



Notes: LTV ratio and DSTI ratio caps on the x-axes are measured in percentages. PDs and LGDs on the y-axes are measured in percentages.

The results for Austria show that the initial baseline PD of 1.7% starts falling from an LTV cap at about 70%; at the left end of the LTV cap grid (50%), the PD falls to 1.2%. LGDs are more reactive, as they start falling from an LTV cap at 90% and then along a more negative slope toward lower LTV caps. The baseline LGD of 16.4% falls to less than 4% under the 50% LTV cap. For the DSTI caps, the PD tends to be more reactive than with the LTV cap, falling to less than 0.2% under the 0.2 DSTI cap. The volume reduction for Austria implied by the LTV caps shows that 74% of the outstanding mortgage amount would be crowded out if the LTV cap was imposed at 50%, as opposed to about 22% at the cap of 120%.

Across all countries, the results can be summarised as follows: first, LTV caps have more potential to reduce LGDs while DSTI caps have more bearing on PDs; this is expected because an LTV ratio is a stock ratio that is closely related to the LGD while DSTI ratios are related to flow variables (income and expense, the latter including debt service) and therefore to PDs. Both types of caps do, however, also reduce the respective other risk parameters through an apparent correlation of stock and flow characteristics at household level. The cross-risk parameter response appears to be more pronounced for the DSTI cap, which also compresses LGDs quite significantly.

3.2 Macroeconomic impact and feedback to household risk parameters

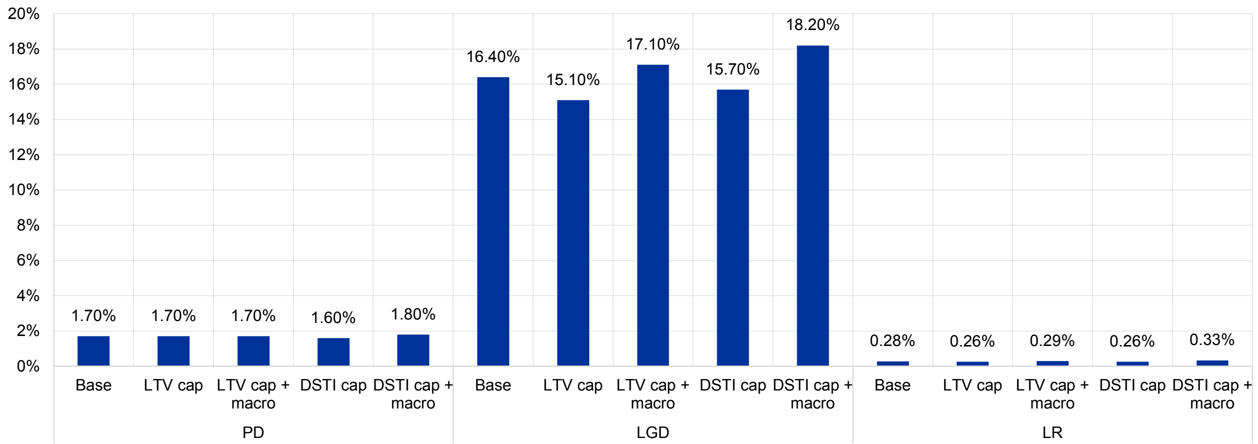
Starting from an assumed LTV cap of 85% for all four countries, the macro feedback effects are estimated, which involves the connection of Module E to Module A for the inclusion of the policy-induced loan demand shock. To identify the impulse as a demand shock, the loan interest rates in the GVAR model are sign-restricted in order for them to fall, along with the volumes in the first quarter of the simulation in the country in which the policy shock originates. The year 2010 was taken as the reference year to compute the loan demand shocks relative to all outstanding loans implied by the LTV cap. The LTV cap-implied shocks for the four countries (Austria, Belgium, Germany and Portugal) amount to -2.3%, -3.4%, -0.9% and -0.5%. In parallel with the LTV cap-implied shocks, the loss rate-equivalent DSTI shocks were simulated, which are smaller compared to the LTV cap-implied volume shocks by a factor of about 0.7 on average across countries.

The results in terms of household sector responses for PDs, LGDs and loss rates are shown in Chart 15.3; again just for two countries as an illustration.

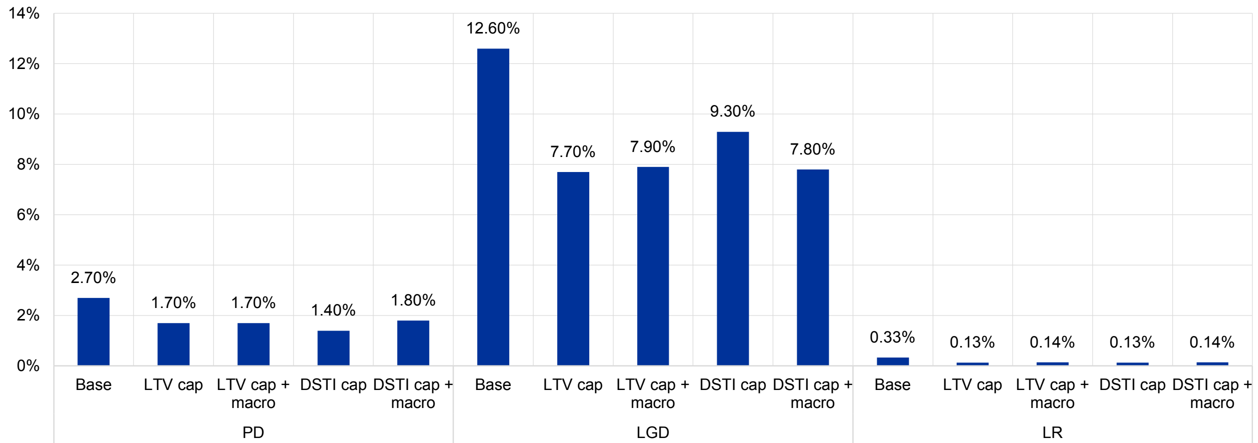
Chart 15.3

Impact of LTV cap at 85%

Austria



Belgium



After the first-round mechanic impact of the imposition of the caps, there is a tendency for PDs to react more to a DSTI cap while LGDs are more responsive to LTV caps. Loss rates after the first round are equal, reflecting the loss rate-equivalence concept. Second-round macro effects can then be seen to be of a somewhat smaller magnitude across countries under the initial DSTI cap policy.

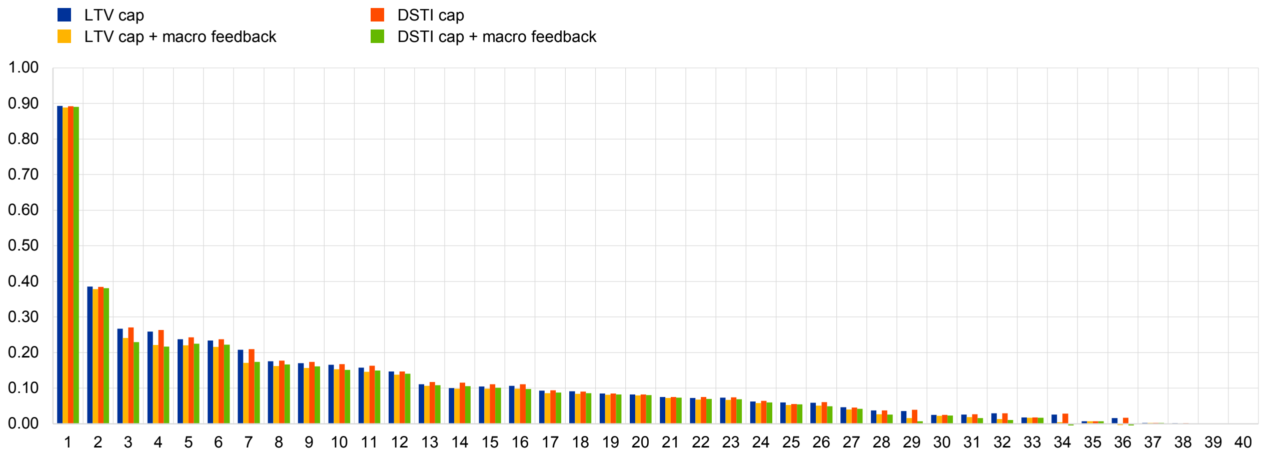
3.3 Impact on banks' capital position

Module F is now used to attach the baseline and policy-conditional risk parameters to the household mortgage portfolios of 40 SSM banks from the four countries for which results were presented thus far.[135] The same one-year horizon is still adopted. The LTV and DSTI cap-implied responses, both excluding and including macro feedback effects, are shown in Chart 15.4.

Chart 15.4

Impact of LTV and DSTI caps on Common Equity Tier 1 position of 40 SSM banks

(CET1 ratio change in percentage points)



The results of the sample of banks are pooled and anonymised. The results suggest that the median CET1 response amounts to 0.08 percentage points, a rather limited effect.

There are a number of banks for which the impact is stronger, however, exceeding 20 basis points and moving up to 0.9 percentage points. The reason that the responses are rather small is that only the mortgage loan portfolios of the banks were included in the simulation. Moreover, the simulation horizon is set to only four quarters.

One conclusion that can be drawn from the model is that households with higher initial LTV ratios are systematically those that are less able to service their debt. That is, PDs (not only LGDs) fall in response to LTV caps, which is not a given, as LTV ratios are related to the leverage of a household balance sheet (i.e. stock measures) and should for that reason exert their impact primarily through LGDs.

Thus, the fact that PDs also fall in response to the imposition of LTV caps means that leverage and the ability to meet periodic debt repayment obligations correlate empirically. Likewise for the opposite case: LGDs fall after imposing a DSTI cap even though their primary impact goes via PDs. In fact, the latter cross-parameter effect for DSTI caps appears to dominate. Hence, DSTI caps can be more effective than LTV caps, in the sense that a certain reduction in household sector loss rates that a policy maker wishes to achieve can be accomplished with a lower reduction in loan volumes when considering the DSTI cap-based policy.

[135] Six banks from Austria, six from Belgium, 25 from Germany and three from Portugal.

4 Conclusions

In this chapter, an integrated micro-macro model has been presented which can be used to assess the responsiveness of household sector risk parameters, i.e. PDs and LGDs, to lending standard-related macroprudential policy measures. More generally, it can be used to translate any macro-financial scenario into household (in particular household mortgage-related) risk parameters, i.e. PDs and LGDs, and be used in conjunction with a bank balance sheet calculation engine to assess the implication of the assumed stress in the household segment for banks.

Irrespective of whether or not LTV or DSTI caps are imposed, the results suggest that PDs and LGDs correlate empirically in the cross-section of households even though there are no structural reasons for this, as house price falls do not imply incentives for strategic default in full recourse systems, which is the predominant structure in European countries. The correlation stems from a positive correlation of DSTIs and LTVs in the cross-section.

A number of extensions to the model are envisaged. First, population growth can be made dynamic, while the current version of the model operates with a static population. Second, the loan supply process can be made endogenous in order for households that do not have a mortgage loan at the outset to be allowed to apply for and be granted a mortgage loan. Third, an explicit distinction between principal and interest repayments can be introduced to make repayment a function of the interest rate developments in a scenario, including the second-round deviations, which is relevant in particular in countries with variable rate regimes.

The first two extensions help allow for a longer assessment horizon, which is currently advised to be set to no more than two years as otherwise the results might be dominated by survivor bias, i.e. PDs fall because high-risk households default on their debt repayment early during the simulation horizon.

Careful attention should, however, be given to finding the right balance between additional model complexity by introducing dynamic population or loan origination features as opposed to a simpler model structure (such as the current one) for the sake of robustness. .

References

Gross, M. and Población, J. (2017), “Assessing the efficacy of borrower-based macroprudential policy using an integrated micro-macro model for European households”, *Economic Modelling*, Vol. 61, pp. 510-528. http://dx.doi.org/10.1016/j.econmod.2016.12.029.

Chapter 16 Prospects for further developments of STAMP€

By Reiner Martin and Dawid Żochowski

The ECB staff top-down stress-testing framework continues to develop and the previous chapters demonstrated that further refinements to the existing toolkit are needed. Importantly, to fulfil its macroprudential role even better, the framework should cover new areas, both in terms of the scope of the financial sectors covered and mechanisms describing interactions between them.

This chapter summarises both types of developments with STAMP€. It begins by setting out some basic features that any macroprudential stress test framework should include. Against this benchmark, it describes which elements of such a framework are already embedded in STAMP€ and which are still to be developed. In addition, this chapter outlines the plans for extending stress testing into other sectors, most prominently the shadow banking sector, but also into the stress testing of central counterparties and insurance and pension funds. It concludes by outlining an ambitious way forward for STAMP€ that would not only contain stress tests of various sectors and the interactions between them, as well as direct and indirect financial contagion, but also attempts to model the financial market players' reactions to stressed conditions that could reinforce each other and lead to possible non-linear price dynamics in funding or asset markets.

1 Introduction

The wider euro area financial sector is becoming more and more diverse and interconnected, increasing the need to develop a fully-fledged macroprudential stress-testing framework. By definition – and this is the key driver of STAMP€ development – macroprudential stress testing goes far beyond traditional stress testing, which focuses solely on the forward-looking assessment of the solvency of individual banks under different scenarios. In the previous chapters of this book, we looked at some important elements of macroprudential stress testing, namely macroeconomic feedback effects (Chapters 10 and 11), contagion impacts within the banking sector (Chapter 12) and beyond (Chapter 13), liquidity stress tests for banks (Chapter 14) and stress tests for households (Chapter 15).

Any macroprudential stress-testing framework should prominently feature the following dimensions: economic agents' behavioural reactions to stress, two-way feedback with the real economy, externalities resulting from interconnectedness, such as fire sales, and broad coverage of financial and non-financial sectors. Looking ahead, STAMP€ will be developed further to take into account all these features, which are clearly relevant for a macroprudential stress-testing framework. This will entail two types of future work. First, improving and extending the parts of

STAMP€ that already exist and second, developing additional modules for the financial and non-financial sectors that are not yet covered by the available framework, including modelling the interactions between them.

Turning to the first type of additional tasks, macroprudential stress tests should account for more realistic features of systemic stress, particularly banks' behavioural reaction to stress, which could come in the form of deleveraging, liability management, capital increases or working out non-performing loans. Typically, banks' individual reactions in a crisis lead to a collective aggravation of the initial stress. To capture this analytically, the dynamic balance sheet, which allows banks to re-optimise their portfolio according to the risk-return optimisation criterion, is a promising route (Hałaj, 2013). There is also a need to develop a realistic modelling of how non-performing loans (NPLs) are managed and how they evolve over time, to the extent that banks, especially in a baseline configuration, decide to actively reduce impaired assets.

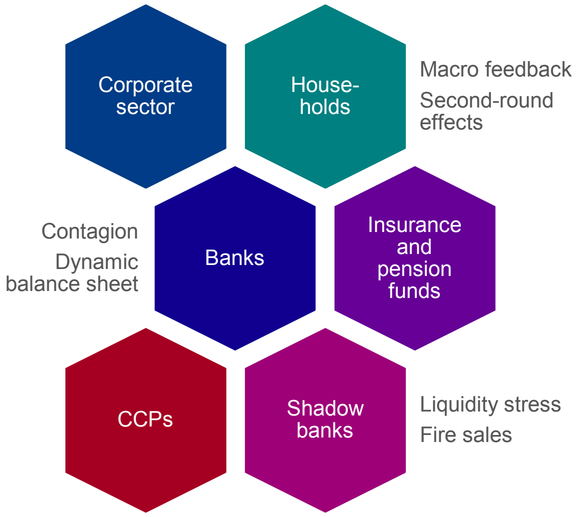
Furthermore, a macroprudential stress test framework should take into account the two-way interactions between banks and the real economy. To this end, STAMP€ already includes macro-feedback effects based on dynamic stochastic general equilibrium (DSGE) models that have been calibrated at the individual country level (see Chapter 10 and Darracq-Pariès, Kok and Rodriguez-Palenzuela, 2011). Another framework employed in STAMP€ is based on a Mixed-Cross-Section Global Vector Autoregressive (MCS-GVAR) model developed by Gross, Kok and Żochowski (2016), which quantifies the macro feedback effects of deleveraging (see Chapter 11).

The macro-feedback nexus is not, however, the only reason why the initial stress can be aggravated at the system-wide level. Contagion effects resulting from interconnectedness and dynamic interactions between financial economic agents can lead to non-linear impacts and, in extreme cases, to fire sales. In fact, the assessment of direct financial contagion via the interbank channel has already been one of the features of the top-down stress-testing framework for some years, and the results of the second-round effects related to possible domino effects in the interbank market are regularly published in the ECB's Financial Stability Review.

However, and this brings us to the second type of forthcoming extensions of STAMP€, macroprudential stress tests should also consider indirect contagion that emerges, for example, from bank-shadow-bank interactions. Agent-based models could be developed further to take into account these interactions and allow for endogenous asset price determination.

More generally, a macroprudential stress test framework should ideally integrate all elements of the wider financial sector (banks, shadow banks, insurers and pension funds, and central counterparties (CCPs), as well as the real economy, to properly account for the various vulnerabilities that may emerge in any sector of the economy, including the household sector and non-financial corporations (NFCs) (see Chart 16.1).

Chart 16.1
Elements of macroprudential stress tests



2 Liquidity and funding stress testing

The global financial crisis demonstrated very clearly the importance of the transmission channels from liquidity and funding to solvency and vice versa. While the liquidity coverage ratio is useful for maintaining sufficient liquidity buffers at the bank level, in a system-wide systemic liquidity stress situation, second-round effects resulting from contagion in the interbank markets and possible fire sales play a prominent role.

Chapter 14 presented the current state of development of the top-down liquidity stress-testing framework, as developed by ECB staff. However, more work needs to be done on integrating the liquidity and funding framework with the solvency stress-testing framework in order to arrive at a more holistic view of the interaction between liquidity and solvency. Irrespective of the origins of the shock to the financial sector, which can be multiple and are largely unpredictable, the major propagation channels between liquidity and solvency are broadly the same, resulting in a number of vicious solvency-liquidity nexuses, including in particular:

Fire sale externalities: fire sales arise due to incomplete markets during times of stress, impacting the solvency of banks and other financial entities via losses on the disposal of assets at fire sale prices and mark-to-market losses on liquid assets held at fair value (asset price channel). Furthermore, the impact of fire sales on asset prices is likely to be non-linear, whereby at some point in the systemic stress, the liquidity in the markets evaporates and the prices of bonds and assets “fall off the cliff”. A proper liquidity stress-testing framework should be capable of assessing such effects, which are likely to be also related to the depth of various market segments and the behavioural reactions of sellers and buyers, also in a form of a herding behaviour.

Margin calls and closure of funding markets: behavioural reactions of funding market participants may also facilitate negative feedback loops, triggered by illiquid banks calling in interbank facilities at other banks or raising margin requirements in repo or derivative markets. The evidence from the global financial crisis suggests that weak institutions could be subject to runs in the funding markets, whereby the institutions face quantity constraints and cannot roll over their debt at any price. This may lead to a market-wide increase in funding costs and/or the closure of the funding markets for individual institutions. In addition, the topology of the network may be important in determining whether, and how quickly, an idiosyncratic shock translates into a system-wide cascade, which, in extreme situations, can lead to the closure of the funding markets for healthy institutions too.

Credit rating: deterioration in a bank's credit rating, triggered by a capital position that has worsened, may lead to higher funding costs, which *ceteris paribus* leads to a further deterioration in the solvency position. This endogeneity is one of the key elements of the integrated solvency-liquidity framework and needs to be modelled explicitly, also taking into account the effect of externalities on the system as a whole.

Asset quality: the worsening of the credit quality of assets leads to a worsening of the cash flow, as non-performing exposures do not generate cash inflows, which, in turn, leads to an immediate deterioration in the liquidity and, going forward, funding position. In addition, poor asset quality, even if only perceived by the markets in situations where transparency is deemed as insufficient, can in itself lead to higher funding costs for banks, which, in turn, leads to a deterioration in their capital position. This feedback loop also needs to be explicitly modelled in an integrated solvency-funding-liquidity framework.

In its currently envisaged final state, the liquidity and funding stress-testing framework embedded within STAMP€ will be based on three layers.

The first layer will focus on banks' capacity to withstand short-term liquidity stresses under a given set of stylised assumptions on the availability of funding, given the liquidity structure of banks' assets, and an estimation of individual banks' counterbalancing capacity, in order to estimate forward-looking and scenario-conditional liquidity shortfalls (see Chapter 14).

The second layer of the framework is based on the network tools that already exist to assess the potential for second-round contagion effects (see Chapter 14). In addition, the framework would include banks' behavioural responses to liquidity shocks to assess the potential for spillover of the shock across the system or amplification mechanisms related, for instance, to cash hoarding.

The third layer of the framework will establish an empirical relationship between banks' solvency and other banks' fundamental characteristics, such as credit rating or the level of non-performing exposures, and funding costs, also taking account of possible non-linearity, whereby banks' funding costs could increase disproportionally with decreasing solvency up to the point where funding markets could close up entirely. This will make it possible to assess how an initial solvency shock could be amplified via funding markets, taking into account the maturity and cost profile of the existing funding.

For such a framework to assume a systemic dimension, funding market conditions may even need to be modelled on the future, scenario-conditional capitalisation of the entire banking sector. In addition, both idiosyncratic and systematic factors in the solvency-funding feedback nexus, including non-linear dynamics, may need to be taken into account in order to fairly reflect funding market conditions under pre-specified stress test scenarios.

3 Stress testing other sectors

As mentioned earlier, STAMP€ should eventually integrate all parts of the wider financial sector, as well as the real economy. Using data from the ECB Household Finance and Consumption Survey, a framework for stress testing the balance sheets of individual households was developed. This framework allows for the computation of probabilities of default and loss given defaults for mortgage exposures based on household sector data and links them to macroeconomic stress scenarios (see Ampudia, Vlokhoven and Żochowski, 2014; and Ampudia, Vlokhoven and Żochowski, 2016). As described in more detail in Chapter 15, such a framework is now being integrated into the top-down stress-testing framework, which will further enhance the consistency of the stress test scenario. The results would then take into account dynamic adjustments of individual households' balance-sheets in response to shocks and related second-round effects (see Gross and Población, 2017). Similar modelling extensions need to be considered also for NFCs given the key role that company sector financing and thereby investment play in the overall macroeconomic picture.

Looking ahead, STAMP€ needs to evolve to include second-round effects from two-way interactions between the banking sector and other parts of the financial sector. The rest of this section describes the progress already made in this direction, as well as future plans for shadow banks, CCPs, and insurance and pension funds.

3.1 Shadow banks

The shadow banking sector in the euro area has grown both in absolute terms and relative to other parts of the wider financial sector (see, for example, ECB, 2016), and it is often argued that it is likely to increase further, owing *inter alia* to the tightening of the regulation of traditional banks (see, for instance, Kashyap, Tsomocos and Vardoulakis, 2014, or Ordoñez and Piguillem, 2015). The growing size of the shadow banking sector and its expansion into business areas typically associated with traditional banking pose increasing analytical challenges for financial stability and for macroprudential policymakers. Recent research suggests that the shadow banking sector has a natural tendency to grow until it becomes systemically important for the entire financial system and endangers the stability of the banking sector (see Ari, Darracq-Pariès, Kok and Żochowski, 2016).

Stress testing shadow banks can help to reveal the vulnerabilities in this part of the wider financial sector and to assess potential spillovers to the rest of the financial sector. As a starting point, the resilience of the largest shadow banks to various stress factors should be assessed. This includes, in particular, resilience to various asset price shocks and to the materialisation of redemption risk. An analytical framework that assesses these risks should include simulations of fire sales that account for the depth and liquidity of various asset markets. Ultimately, the shadow bank stress-testing framework should be integrated into the banking sector stress-testing framework by taking into account various layers of interconnectedness, identifying both direct and indirect contagion channels.

At this point in time, efforts are being made to get hold of sufficiently granular data that allows for the credible stress testing of shadow banks. At the same time, various layers of interconnectedness are modelled, in order to identify the direct and indirect contagion channels. More specifically, a reliable stress-testing framework for shadow banks should consist of the following elements:

1. Aggregate stress tests. This involves reconstructing the aggregated balance sheets of the main types of euro area shadow bank institutions, i.e. money market funds, investment funds and special investment vehicles, and conducting simple macro stress tests that look at the impact of various asset price shocks on shadow banks' equity.

2. Firm-level stress tests. There is a need to assess the asset portfolio allocation of individual investment funds, using micro-level data. This will allow firm-level stress tests, also taking exposures to common asset markets via the overlapping portfolio channel into account.

3. Fire sale simulation. In this work stream, the scope of possible fire sales is assessed in an agent-based system of banks and shadow banks, along with asset prices (see Calimani, Hałaj and Żochowski, 2017). In such a set-up, an initial exogenous liquidity shock may lead to a fire sale spiral. As the price of the security decreases, both agents update their equity and adjust their balance sheets by making decisions on whether to sell or buy the security. This endogenous process may trigger a cascade of sales leading to a fire sale. The calibration of this theoretical model will account for the depth and liquidity of various asset markets.

4. Interconnectedness. A framework is needed for modelling the interconnectedness of banks and shadow banks, which could be obtained by identifying direct and indirect contagion channels. To this end, an agent-based network of banks and shadow banks (via equity, funding linkages and exposures to common asset markets) could be put together. Then, the knock-on effects on banks of redemptions in the shadow banking sector could be simulated, e.g. to assess the impact on banks' capital ratios and lending to the real economy.

3.2 Central counterparties

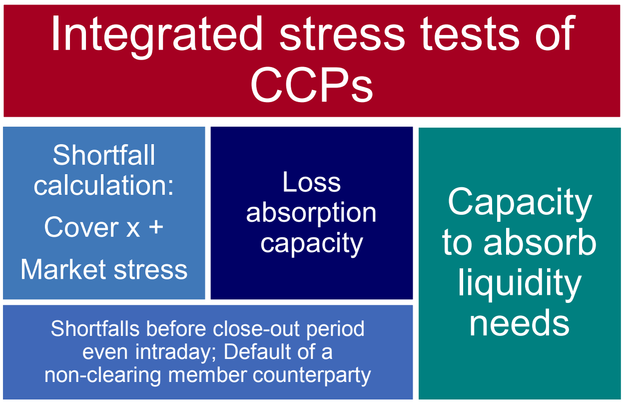
CCPs were set up to reduce systemic risk stemming from bilateral counterparty connections owing to the fact that trading activity carried out both over the counter and on trading venues forms a network in which idiosyncratic shocks can result in a cascade of defaults among interconnected counterparties.

The very nature of CCPs requires a somewhat different approach to stress testing and scenario design compared to the approaches typically applied to scenarios for bank or insurance stress tests. Given that CCPs are the counterparty to all their clearing members, forming a star-type network, they are super-systemic, as their default could endanger the entire financial system. For this reason, CCPs are designed to be very resilient. The European Market Infrastructure Regulation (EMIR) and the related Regulatory Technical Standards (RTS) require, for example, CCPs to have sufficient margin collateral to cover price risk up to the value at risk at the 99% confidence level for other than OTC derivative contracts and 99.5% forall OTC instruments, while plausible stress above those levels must be covered by the mutualised guarantee fund.

CCP stress tests thus require a rather severe scenario over a very short-term horizon of two to five days. In a more traditional scenario, where economic and financial risk factors are interlinked using historical dependencies, it is challenging to arrive at a consistent scenario that would be sufficiently severe from a CCP stress test perspective. To overcome that challenge, a novel approach to scenario design needs to be employed. While maintaining historical dependencies between risk factors, shocks are derived based on observations from shorter time-horizon samples, focusing on periods of stress in certain market segments, e.g. during and shortly after the collapse of Lehman Brothers. This yields extreme, yet plausible and consistent, scenarios for these specific market segments.

Chart 16.2

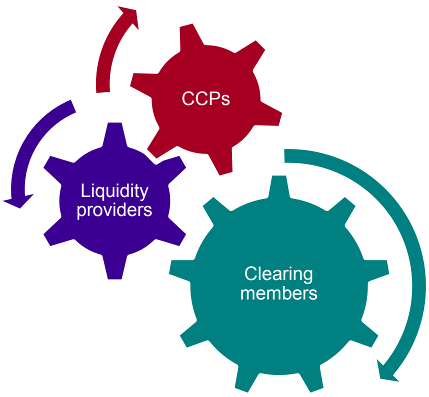
Liquidity stress is crucial to account for the vulnerabilities of the CCP system



Source: Authors' analysis.

Chart 16.3

A web of networks – interlinkages in the CCP network



Source: Authors' analysis.

In addition, CCP stress tests need to cover both solvency and liquidity elements, as shortfalls before close-out periods resulting from intraday positions in the aftermath of a clearing member default can add to the overall CCP losses (see Chart 16.2). In a similar vein, CCP stress tests need to take into account the potential for large contagion to spread across all parts of the wider financial sector. This is not only because CCPs are interlinked via interoperability arrangements but also because clearing members may act as liquidity providers or investment counterparties to CCPs, as well as interacting with one another (see Chart 16.3).

A relevant framework should then comprise a network of networks, for which, beyond the complexity of the structure, data would be difficult to gather. The specific time dimension of the stress via CCPs also renders the connection with a banking sector solvency framework challenging, for which stress tests usually are not meant to lead to a generalised collapse of all financial intermediaries. Such crisis situations, such as liquidity crises, still need be analysed, possibly with a specific toolkit.

3.3 Pension funds and insurance companies

Pension funds and insurance companies are characterised by business models with guarantees on long-term liabilities. This is particularly relevant for life insurers, who traditionally offer products with a minimum investment return and defined-benefit pension funds. In addition, unlike the banking sector, in these sectors liabilities have a longer average duration than assets. For these two reasons, the current low interest rate environment poses a gradually increasing challenge for the sustainability of the business models of these institutions, as maturing assets are re-invested in lower-yielding securities. Against this background, assessing the vulnerabilities of these sectors using stress tests has gained importance in recent years.[136]

In addition, the capacity of these two sectors to act as long-term buy-and-hold investors, stabilising financial markets by providing a cushion against adverse price changes, may have decreased as the balance sheet of these institutions weakened. This speaks in favour of possible stronger second-round effects from stress in the insurance and pension fund market for the wider financial sector. Hence, there is an increasing need to integrate these sectors into a broader macroprudential stress-testing framework beyond purely sector-specific stress tests.

Against this background, next to a plain vanilla top-down approach to stress testing insurers, a stochastic model to assess the profitability and solvency of European insurers in a forward-looking manner is needed. In this framework, representative insurance balance sheets calibrated at the country level are projected forward to assess the vulnerabilities of the sectors to a prolonged period of low interest rates (see Berdin, Pancaro and Kok, 2017). The model is flexible and allows the impact of other possible scenarios to be assessed.

[136] Recognising these challenges, the European Insurance and Occupational Pensions Authority (EIOPA) conducted Insurance Stress Tests in 2011, 2014 and 2016, as well as the Occupational Pensions Stress Test in 2015.

4 Possible way(s) forward

For macroprudential stress tests, further analytical work that goes beyond bank-by-bank solvency and liquidity stress tests is necessary. There is a need to stress test other parts of the financial sector and the macro economy, including shadow banks, insurance corporations and pension funds, CCPs, households and corporates in order to obtain a more complete and holistic assessment of how financial and economic risks may materialise. While work has already started on most of these fronts, development and finalisation will require time, not least because new priorities may arise or modelling difficulties appear.

In the run-up to the start of the financial crisis in 2007/2008, it was mainly private sector debt that increased materially, while sovereign debt remained broadly unchanged. Hence, the imbalances originated in the household sector, while public debt remained flat in real terms well into the crisis. Empirical findings indeed suggest that a financial crisis more frequently follows excessive indebtedness in the private sector. In particular, housing and real estate cycles are at the core of the financial cycles. From a historical perspective, roughly one-third of banking crises were preceded by a credit boom (see Valencia and Laeven, 2012).

A fully fledged macroprudential stress test framework, in line with what is presented in this chapter and in some of the earlier chapters of this book, could be used to assess the resilience of households' or corporates' balance sheets to systemic vulnerabilities before they materialise. This is also important from a macroprudential policy perspective, given that the macroprudential policy toolkit includes tools that can be used to prevent, or at least dampen, the build-up of vulnerabilities that can lead to financial crises, for instance, caps on loan-to-income and loan-to-value ratios.

In addition, more work is needed on the reactions of market participants to stress. For instance, bank stress tests tend to assume a static balance sheet, which suggests that banks are not undertaking management actions aimed, for example, at re-optimising their portfolios in line with the new stressed conditions. STAMP€ already takes into account a dynamic balance sheet for both assets and funding. Nevertheless, more work is needed to allow for the reactions of other market participants to stress. In this connection, it would be useful to conduct agent-based model simulations with parameters calibrated using both macro and micro data and informed by surveys. Further work could also include modelling shadow bank reactions to redemptions and abrupt asset price shifts. In addition, it seems key to find a way to model the reactions of CCPs to clearing members' defaults. The ultimate ambition may be to simulate possible feedback and amplification mechanisms in a multilayer network including CCPs, clearing members, liquidity providers and investment counterparties.

To conclude, in a system-wide macroprudential stress-testing framework, all channels of financial contagion, both direct and indirect, between all key macro-financial sectors ideally need to be included. This is a challenging and possibly unattainable goal. At the same time, good progress has already been made by ECB staff over the last three years in extending and further developing their top-down stress-testing framework. Filling out the remaining dimensions of macroprudential stress tests, as well as deepening the integration between the various parts, represents a dense and ambitious work programme going forward.

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