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Making supervisory stress tests more macroprudential: Considering liquidity and solvency interactions and systemic risk

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List of abbreviations

2SLS	Two-stage least squares
3SLS	Three-stage least squares
ABCP	Asset-backed commercial paper
ABM	Agent based modelling
AFS	Available for sale
ASF	Available stable funding
BCBS	Basel Committee on Banking Supervision
CCA	Contingent claims analysis
CCP	Central counterparty
CDS	Credit default swaps
CFP	Contingent funding plan
CET1	Common Equity Tier 1
CLO	Collateralised loan obligation
CT1	Core Tier 1
DFAST	Dodd-Frank Act Stress Testing
DSGE	Dynamic stochastic general equilibrium
DVA	Debit valuation adjustment
EDF	Expected default frequency
ERMS	Enterprise risk management solution
ES	Expected shortfall
FSAP	Financial Stability Assessment Program
FSR	Financial Stability Report
FTP	Funds transfer pricing
FVCDS	Fair value credit default swaps
GCF	General collateral finance
GLS	Generalised least squares
HQLA	Hiqh quality liquid assets
IMF	International Monetary Fund
ISDA	International Swaps and Derivatives Association
LCR	Liquidity coverage ratio
LGD	Loss given default
LIBOR-OIS	London Interbank Offered Rate – Overnight Indexed Swap Rate
LLP	Loan loss provision
LR	Leverage ratio

MBS	Mortgage-backed security
MFRAF	Macro-Financial Risk Assessment Framework
MMF	Money market fund
Nibor	Norwegian Interbank Offered Rate
NIRatio	Net income as a percentage of total assets
NSFR	Net stable funding ratio
OLS	Ordinary least squares
PD	Probability of default
PFLOAT	Puttable Floating Option Tax-Exempt Receipts
QIS	Quantitative Impact Study
RAMSI	Risk Assessment Model for Systemic Institutions
RBC	Risk-based capital
RMBS	Residential mortgage-backed securities
RWA	Risk-weighted assets
SAMP	Systemic Risk Assessment Model for Macroprudential Policy
SPV	Special purpose vehicle
VAR	Vector Auto Regression
VIX	Global risk aversion

1. Motivation and summary[1]

In the run-up to the financial crisis of 2008–09, banking supervisors had largely followed a microprudential approach towards assessing banks. As such, many of the "first-generation" stress tests used by bank supervisors after the crisis were data-heavy bottom-up exercises that focused on solvency risks. Some supervisors also considered liquidity risks, but these risks were often viewed as independent of solvency risks, to be estimated separately. Additionally, authorities' stress tests often did not consider the potential interlinkages in the banking system or ways in which bank behaviour might collectively prove destabilising to the financial system.

However, as the crisis attests, the failure to adequately model interlinkages and the nexus between solvency risk and liquidity risk within and across banks led to a dramatic underestimation of the risks to, and vulnerabilities of, financial systems in many economies. The prior Basel Committee working paper of the RTF liquidity stress testing (LST) work stream contains a summary of case studies, which discusses some liquidity and solvency interactions at large banks, such as Lehman, RBS, Dexia and Wachovia.[2]

With the global financial crisis now past, supervisors have been busy both reflecting on the reasons behind the explosive growth of interlinkages in the run-up to the crisis as well as developing new stress testing models and tools to assess financial stability taking into account interconnectedness among institutions and the interplay between credit and liquidity risk at a system-wide level. As regards the former, a key foundational reason put forth for the "financial globalisation" prior to the crisis was the active pursuit of complete markets by regulators in many of the advanced economies.[3] While the exact rationale for why complete markets were viewed favourably is beyond the scope of this paper, an important outcome, nevertheless, has been the innovation of new hedging strategies, complex structured financial products and greater interconnectedness. As regards the latter, supervisory stress testing models are now starting to move beyond traditional bilateral counterparty analysis to more sophisticated supervisory approaches to considering both asset and funding interlinkages and how changes in behaviour could be destabilising. Inclusion of liquidity in a stress testing model facilitates the consideration of contagion risks. Research on interbank networks points to several possible channels of systemic risk and contagion, with two of the leading channels being: runs and liability linkages between financial institutions, and asset firesale risk of banks' securities portfolios, both of which are considered when a stress testing model is broadened to analyse liquidity risk.

As shown during the 2008–09 crisis, (potential) shocks can be amplified through several channels. These channels include overexposure of the financial system to credit shocks, as well as asset fire sales and high interconnectedness. Supervisory stress testing conducted in a microprudential manner, while beneficial, tends to focus largely on the safety and soundness of *individual* institutions and could miss key tail risks. For example, supervisors can fail to discern the build-up of risk across the financial system, either through common exposures, failure to consider the reaction function of other banks in a stress scenario or in light of actions of parts of the non-bank financial system outside of bank regulators' immediate purview. Hanson et al (2011) point out that such a pre-crisis microprudential

1 Drafted by K Anand (Bank of Canada), J Cetina (Office of Financial Research) and I van Lelyveld (Netherlands Bank).

2 See BCBS (2013a).

3 See Gopinath (2010).

regulatory mindset was, largely, a partial-equilibrium one, aimed at safeguarding individual financial institutions.

This argues for applying a macroprudential approach to stress testing as a key complement to the standard bottom-up supervisory stress testing. Such macroprudential thinking focuses more on general equilibrium effects and is concerned with safeguarding the financial system as a whole. For example, Crockett (2000) helpfully offers the interpretation of peer group analysis as a concrete example of how microprudential and macroprudential supervisory perspectives differ. Whereas a microprudential supervisor conducts peer analysis with an eye towards identifying those institutions deviating from peers (idiosyncratic risk), a macroprudential supervisor might instead view all institutions following the same strategy as a source of concern. This shift from a microprudential to a macroprudential policy perspective among bank supervisors parallels developments in macroeconomics and macroeconomic policymaking following the critique of Lucas (1976), who argued that policies derived from models without endogenous reactions of agents would be misleading. Indeed, the International Monetary Fund (IMF), in its 2014 *Review of the Financial Sector Assessment Program* (FSAP), underscores the need to strengthen the systemic focus of the financial stability assessment, deepen the analytical treatment of interconnectedness, expand coverage of stress tests to non-bank financial sectors and enhance the systematic analysis of cross-border spillovers (IMF (2014)). The Basel Committee's *Principles for sound stress testing practices and supervision*[4] also recommend that banks take into account system-wide interactions and feedback effects (principle 8), and consider interactions between funding and liquidity (principle 10).

Building on the experiences of different countries, this paper suggests that authorities should emphasise developing integrated liquidity and solvency stress tests (as opposed to stand-alone liquidity stress test exercises). Arguably, a lesson from the crisis, which involved the realisation of credit risk in structured credit products as well as substantial maturity transformation by banks in off-balance sheet structured investment vehicles (SIVs), is that there are benefits to considering both risks in an integrated manner.

The paper offers several approaches to incorporating liquidity effects and their interactions with solvency that differ in their level of comprehensiveness and sophistication. In particular, the paper offers contributions to three key areas. First, micro stress tests provide a basis for developing and enriching stress tests by considering channels in addition to the standard credit channel through which shocks can be transmitted (and by trying to evaluate liquidity and solvency interactions). Second, an analysis of estimated interactions between liquidity and solvency risks, using both regulatory and market-based measures, at the micro level will help improve stress testing models for individual banks. Using these micro approaches, authorities will be better able to assess the health of an individual bank under alternative risk scenarios and identify vulnerabilities. Finally, the third layer – network analysis and agent-based models – proves useful for broadening stress tests, as these models consider contagion through common exposure, interbank funding relationships and the endogenous behaviour of banks. Network analysis and agent-based models offer insights into the ways banks (and other financial system agents) interact and the ways shocks can propagate in the financial system.

The paper's key messages are that integrated liquidity and solvency stress tests (as opposed to stand-alone liquidity stress test exercises) are desirable, as liquidity and solvency interactions can be material. Approaches exist for capturing these interactions and, in some instances, have already been implemented by supervisors. While this paper offers contributions on the topics of channels, liquidity and solvency interactions, and potential systemic spillovers, work stream members note that two important areas remain in need of additional research to strengthen supervisory stress tests: estimating

[4] See BCBS (2009).

the evolution of banks' balance sheets under stress, and modelling feedback between the financial sector and the macroeconomy.

1.1 Summary of key sections

The paper starts with an overview of the channels of interaction between liquidity and solvency (Section 2), considers some opportunities to strengthen liquidity and solvency interactions in supervisory stress tests (Section 3), outlines some existing supervisory stress tests that employ techniques that consider both liquidity and solvency interactions as well as systemic risk (Section 4), and then discusses the use of network analysis and agent-based models in stress tests (and in policy analysis) to evaluate systemic risk (Section 5).

The key points from the RTF working paper on supervisory stress tests are summarised in Table 1.

Key points from RTF working paper on supervisory stress tests — Table 1

Section	Problems considered	Takeaways	Potential input for supervisors
Section 2 Taxonomy of channels of bank stress	Typology of shocks (credit, funding, liquidity, collateral), potential transmission channels via deleveraging as various bank regulatory ratios (RBC, LR, LCR, NSFR) bind.	Deleveraging/asset fire sales can result from capital or liquidity ratios becoming binding. The NSFR is most sensitive to a broad array of shocks, as it incorporates both capital and funding elements. Deleveraging strategies can vary somewhat depending on which regulatory ratio is binding.	Framework for considering multiple types of stress for scenario design and possible amplification mechanisms via asset fire sales. Potential heuristics for agent-based model.
Section 3 Solvency and funding cost interactions	Review of existing empirical literature on bank solvency and funding cost and/or quantity interactions and new RTF-LST cross-country empirical work on bank solvency and funding cost interactions.	Interaction between solvency and funding costs is statistically and economically significant and set simultaneously. Stress tests which consider both capture observable dynamics. RTF-LST model can be replicated by national supervisors using own data, or estimated coefficients can be used to parameterise stress tests.	The existing literature suggests 26 bp to 100 bp lower funding costs per 100 bp increase in the solvency ratio. RTF-LST's own study finds a higher interdependence (112–141 bp decrease in funding costs per 100 bp increase in CT1 ratio; and 100 bp increase in funding costs associated with about a 30 bp reduction in CT1 ratio).
Section 3 Merton model insights	RBC ratios are but one factor determining insolvency risk. Implied ratings derived through CCA can enrich supervisors' consideration of risks to banks' solvency and potential funding stress. CCA is used in, for example, the IMF's Financial Sector Assessment Program.	RTF-LST used stress test data to assess whether RBC ratios and CCA results presented comparable stories. CCA yielded different insights in terms of stressed banks from regulatory ratios where stress under the CCA framework is defined as a bank's transition to a sub-investment grade rating.	Supervisors could ask reporting banks to provide estimates for share price (a key input in a CCA model) and/or estimated rating under stress scenarios to gauge potential for severe shock to rating that triggers withdrawal of wholesale funding.

Key points from RTF working paper on supervisory stress tests — Table 1

Section	Problems considered	Takeaways	Potential input for supervisors
Section 4 Supervisory model overview	Section summarises supervisory stress tests of RTF-LST members with liquidity/solvency interactions and systemic feedback effects, and quantifies the relative importance of these effects for total stress test outcomes.	One supervisory model shows liquidity risk, and contagion pushes out the tail of banking system losses in the stress scenario relative to credit losses only; another supervisory model shows that the overall impact of stress scenarios would be substantially underestimated (approximately 30%) if solvency is considered in isolation from liquidity risk.	Descriptions of relevant RTF-LST supervisory models with interactions provide some starting points for other supervisors seeking to consider ways of incorporating liquidity risk and second-round effects.
Section 5 Network analysis	Network analysis is superior to analysis of bilateral exposures in terms of evaluating contagion risks. The section compares the performance of different partial network models using complete data from 23 financial networks from 12 countries.[1] Partial network models are necessary when supervisors lack complete data.	The choice of the algorithm for network reconstruction when data are partial should be based on supervisors' knowledge of the general structure of the particular market being assessed for contagion risk (CDS, interbank lending, repo, payment system, etc). Observed bilateral matrices can be approximated quite well even with limited information.	The section provides supervisors with a basis for selecting a partial network model from the literature when they have only limited data. The section suggests which models are best with partial data when the true networks are thought to be sparse versus dense and when the true networks are thought to be more or less concentrated.
Section 5 Agent-based models (ABM)	ABMs offer a mechanism for integrating banks' behavioural reaction functions into stress tests. For supervisors with purviews that include non-banks, ABMs offer the potential for an integrated financial system stress test.	More useful as a tool for macroprudential supervision/financial stability monitoring than strictly microprudential supervision of banks but are very helpful in that they move analysis in the direction of a general equilibrium approach.	RTF-LST members provide two examples of ABM approaches which could benefit stress testing. These models are complex and remain a research frontier for stress testing.

[1] The work stream has compared the performance of several algorithms in the literature for deriving the true network, in terms of topological measures and measures of risk. First, members collected data for complete networks for several countries. They next postulated for each of these networks that they only knew the total amounts lent and borrowed by each bank, ie they computed the marginals as though they had partial data. Using these marginals, work stream members estimated the true networks, employing several different methods to derive them. Finally, the estimated network matrices were compared to the original network to evaluate the performance of the different methods.

An important first step is to develop a taxonomy for the channels through which liquidity risk and solvency risk interactions may occur. This is presented in **Section 2**. This taxonomy will enable supervisors tasked with developing stress tests to broaden the types of shocks considered, enrich feedback effects and develop heuristics for agent-based models (discussed in **Section 5**). Examples of channels include, but are not limited to, asset fire sales, illiquid banks pulling funding from other banks, commitments being drawn, collateralised loan obligation (CLO) pipeline back-ups, and credit rating downgrades pressuring banks' funding costs, funding availability and solvency. Additionally, of the Basel III regulatory ratios, the net stable funding ratio (NSFR) is sensitive to the broadest range of shocks, as it incorporates both funding and capital elements. Further, the inclusion of liquidity shocks in stress tests could provide more comprehensive coverage of the risks to a firm's capital adequacy under stress, because a bank's risk-based capital ratio or leverage ratio could be breached as a result of unanticipated balance sheet growth. Such regulatory links could argue for the development of liquidity and solvency interactions in supervisory stress tests merely for purposes of arriving at a better estimation of individual institutions' regulatory compliance under stress, ie taking solely a microprudential perspective.

Section 3 considers several simple ways in which liquidity and solvency interactions can be better estimated in supervisory stress tests. First, the section provides a short summary of the key empirical literature on liquidity and solvency interactions with an emphasis on useful lessons for practitioners. A key lesson from the 2008–09 crisis is that funding and market liquidity risks are intrinsically related to leverage, credit risks and market prices. Thus, it is vital to treat liquidity and solvency risks as interacting risks.

Additionally, this section presents some work stream results using a simultaneous equation model which attempts to account for the endogeneity of liquidity and solvency positions of banks using a panel of international banks. This empirical work yields three core insights. First, regulatory solvency ratios and bank funding costs are not independent, but determined simultaneously. Second, the econometric results confirm the outcomes of the supervisory stress test models of solvency and liquidity interaction discussed in Section 4. The economically significant feedback effects between liquidity and solvency are not artefacts of the modelling assumptions employed, but capture observable dynamics. Stress test models that do not take into account the interaction between solvency and liquidity are likely to underestimate the impact of stress on financial stability. Third, the coefficients of net income and the core tier 1 (CT1) ratio can be used to better parameterise the implications of solvency stress on bank funding costs in supervisory stress tests.

Finally, several work stream members present their use of a contingent claims analysis (CCA) model to estimate the ratings transition of banks during the supervisory stress test horizon.[5] Such estimates of banks' ratings migration can be used to inform estimates of funding costs and funding run-off under stress and can provide an alternative market-based perspective on solvency relative to the accounting-based measures used to define regulatory capital.

Section 4 of the paper summarises a new generation of macroprudential supervisory stress test models, which either contain liquidity and solvency interactions and/or network modules to consider contagion and systemic risk. The section also provides some attribution analysis with respect to the importance of including these effects in supervisory model outcomes. It shows that disregarding the interaction between funding costs and solvency can cause the impact of stand-alone liquidity or solvency stress tests to be underestimated by between 30 and 50% under standard stress scenarios.

Finally, an area in need of further refinement in supervisory stress tests is balance sheet assumptions. For simplicity, many supervisors assume a constant balance sheet or use firms' estimates subject to some supervisory review. This section summarises some pioneering work on approaches to identify the goals and constraints that could underpin balance sheet optimisation in supervisory stress tests. However, estimating dynamic changes to a bank's balance sheet under stress remains an area of active research.

Section 5 discusses supervisors' potential use of network analysis and agent-based models. Network analysis allows supervisors to view exposures not on a counterparty by counterparty basis, but by considering how credit and funding risk might propagate given the network of bilateral or even

5 The CCA approach, also referred to as a Merton model, assumes that a firm is solvent as long as the value of its assets is greater than its liabilities. However, the value of the assets is unobservable so the model uses the market capitalisation to impute this value. The key insight of a CCA/Merton-type framework is that the equity of the firm can be viewed as a call option on the total assets of the firm, where the strike price is equal to its liabilities. As with all option-pricing models, realised share price volatility is also a key parameter in a Merton model.

centrally cleared exposures. The failure of one or more banks in a stress test might have implications for other banks through credit or funding channels if they are exposed to banks that, in turn, are creditors of the failing institutions. Thus, network analysis moves supervisors towards a more systemic view – a deeper understanding of which institutions are central or peripheral in a crisis – and is a material improvement on bilateral exposure data in evaluating potential second-round effects on other institutions from credit or funding shocks.

As will be discussed in more detail, when data regarding the full network are readily available, such analysis is largely assumption-free and merely a more holistic way of understanding risk propagation. However, data regarding the network of banks' exposures are often missing or only partially available. In that case, assumptions about the missing data are needed to conduct the network analysis of risks. In this paper, work stream members evaluate various methods to estimate networks suggested in the literature by comparing estimates with actual networks (for networks where all links are known). This provides important perspective for supervisors regarding which models tend to generate outcomes most similar to the true network. Moreover, key network metrics are presented for a wide range of network types.

Agent-based models (ABM) use network data but take the analysis a step further. Specifically, ABMs include behavioural assumptions for how banks' actions in subsequent periods might impact other banks, credit intermediation and economic activity. ABMs can thus guide the use of macroprudential policy to contain systemic risk. Section 5.3 contains an overview of implementation issues and discusses two work stream members' applications of these tools to stress testing.

The paper also contains three appendices, which provide greater detail on some of the topics addressed in the paper. Specifically, Appendix A contains short write-ups of each of the supervisory stress test models discussed in **Section 4**; Appendix B contains more details on the partial network model exercise discussed in **Section 5**; Appendix C contains more details on the bank data used in the empirics of the interaction between solvency and funding costs for large international banks, as discussed in **Section 3**.

2. Taxonomy of channels through which liquidity and solvency interactions can manifest

2.1 Taxonomies of shocks, regulatory constraints and behavioural responses[6]

Building an integrated stress test for liquidity and solvency risks is challenging, in part because of the difficulty in defining possible channels for interaction to occur. This section of the paper presents some members' work on these interactions.

Examples of key interactions from the 2008–09 crisis include, but are not limited to, loan commitments being drawn down, CLO pipeline back-ups, asset fire sales, credit rating downgrades pressuring banks' funding costs, funding availability and solvency, and illiquid banks pulling funding from other banks. This section of the paper provides some structure for thinking about shocks – such as commitment drawdowns, mortgage putbacks, securitisation pipeline back-ups and the loss of funding – which can be missed if supervisors focus solely on credit stress. Additionally, the framework illustrates how these different shocks can result in banks engaging in behaviour to avoid breaches of regulatory

[6] Drafted by J Cetina (Office of Financial Research) and T Pausch (Deutsche Bundesbank).

ratios that, in the extreme, can result in deleveraging and asset fire sales. Less extreme actions by banks can create systemic feedback effects, as banks may attempt to adjust cash flows to minimise the risk of breaching a regulatory ratio. Such actions could include reduced interbank lending, reduced credit intermediation to the economy or hoarding of collateral.

Banks engage in several key intermediation functions: credit transformation, maturity transformation, liquidity transformation and collateral transformation. Each of these intermediation functions creates, in turn, potential channels of stress – a credit channel, a funding channel, a liquidity channel and a collateral channel – through which stress can be transmitted to the bank. The distinction between the funding and liquidity channels is subtle but important. The funding channel refers to risks that arise as a result of changes in the price, term, mix or, in the extreme, ongoing availability of funding to the bank. The liquidity channel refers to unanticipated growth in a bank's balance sheet arising from the items like commitments, a back-up in its loan securitisation or syndication pipelines, or the exercise of liquidity puts.

The necessity that banks comply with multiple regulatory constraints – most prominently risk-based capital (RBC), the leverage ratio (LR), the net stable funding ratio (NSFR) and the liquidity coverage ratio (LCR) – also creates some behavioural responses on the part of banks to shocks emanating from different channels to prevent one or more regulatory ratios from being breached. While regulatory ratios do play a useful role in constraining bank risk-taking, developing a stronger understanding of potential bank responses to the threat of breaching a regulatory ratio is important, as it helps supervisors to consider how the responses of individual banks under stress could place stress on other banks and magnify the overall stress on the banking system.

Table 2 offers a typology of shocks and the regulatory ratios under Basel III that can become binding on banks when these shocks are realised.

Typology of shocks and key regulatory constraints which can become binding

Table 2

Shocks	Credit	Funding	Liquidity	Collateral
	Risk-weight migration, Credit loss hits capital, Increase in	Maturities shorten, mix changes, funding run-off or "run-in"	Commitments drawn, securitisation backup, liquidity puts exercised	Securities prices fall
Regulatory ratio constraints affected	Risk-based capital ratio		Risk-based capital ratio	Risk-based capital ratio
	Leverage ratio	Leverage ratio	Leverage ratio	
		Liquidity coverage ratio	Liquidity coverage ratio	Liquidity coverage ratio
	Net stable funding ratio	Net stable funding ratio	Net stable funding ratio	Net stable funding ratio

Source: OFR analysis.

Table 2 yields several important observations. First, the NSFR is affected by all four types of shocks because it incorporates both capital and funding in its calculation. Second, liquidity shocks can potentially impact all four of the key Basel regulatory ratios, yet they are not consistently incorporated into stress test scenarios. Finally, the addition of liquidity shocks to the suite of supervisory scenarios would provide more comprehensive coverage of risks to a firm's capital adequacy in a stress scenario because a bank's RBC ratio or LR could be breached due to unanticipated balance sheet growth. Currently, most bottom-up supervisory stress tests focus solely on **credit shocks** (the credit channel) and the associated implications of a credit shock for RBC. However, credit shocks also directly impact banks' LR and NSFR. Specifically, capital losses and/or higher provisions could reduce capital and thus worsen banks' LRs. Reductions in capital would also affect banks' available stable funding (ASF) and thus lower their NSFR.

Funding shocks can take multiple forms. Shocks to banks' funding costs can affect banks' earnings. Changes in the maturity or composition of banks' funding can result in non-compliance with the LCR and NSFR. Greater use of repo funding or even a surge in deposits (to a (relatively) healthy bank during a crisis) could adversely affect compliance with the LR. From Table 2, one can observe that RBC is not directly affected in a funding shock, although deleveraging could negatively impact capital.

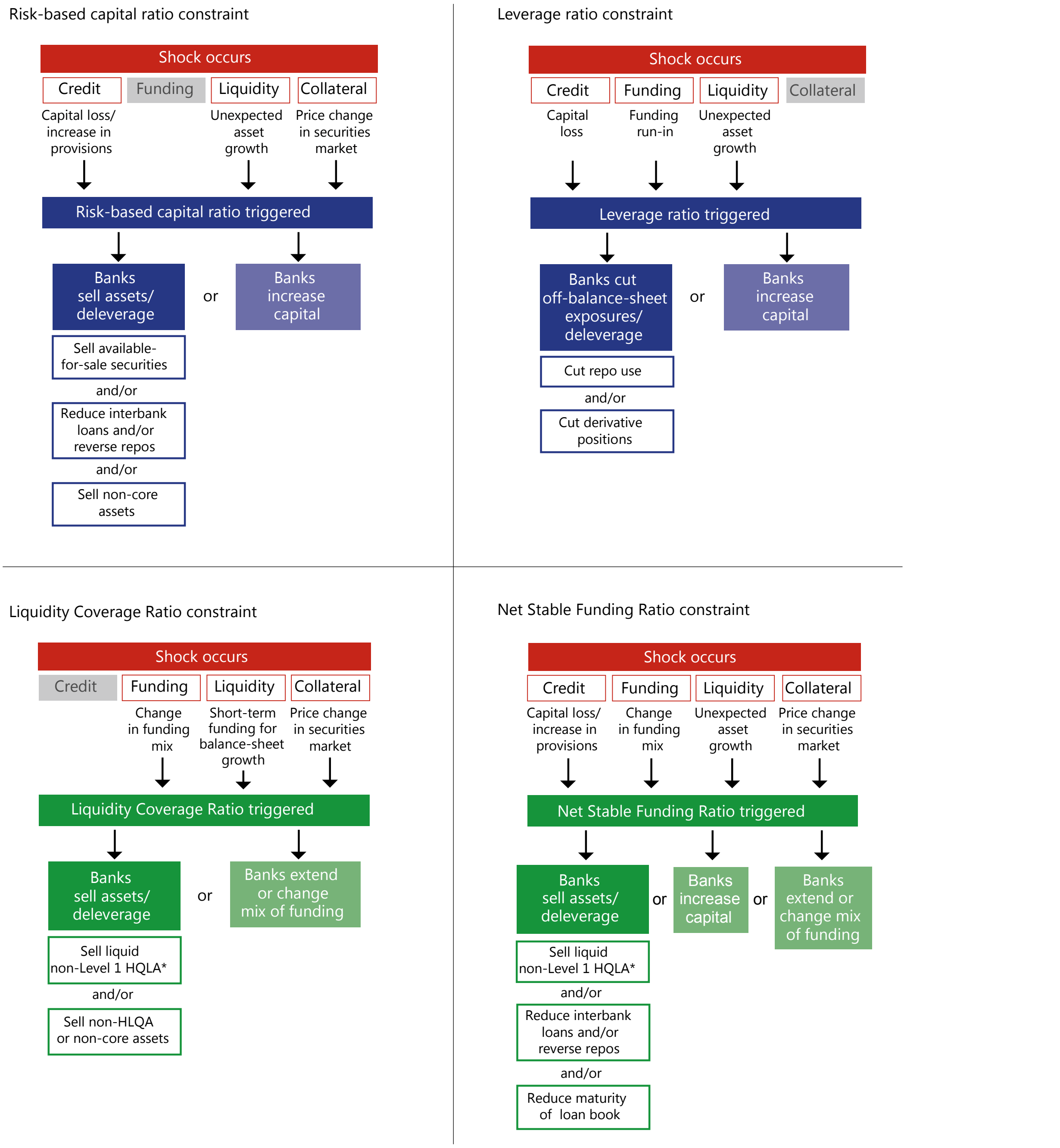
Liquidity shocks, such as a back-up in a bank's CLO pipeline, mortgage putbacks, participation in a CCP auction of a failed clearing member's positions, or the drawdown of liquidity puts, can adversely affect a bank's RBC, NSFR and LR as a result of balance sheet growth. In practical terms, banks generally respond to unanticipated balance sheet growth by making use of short-term wholesale funding, which could put them at risk of breaching their LCR as well.

As illustrated in Table 2, **collateral shocks** can also have direct impacts on several regulatory ratios. Specifically, changes under Basel III to allow unrealised gains and losses to flow through to RBC and high-quality liquid assets (HQLA) are marked to market under the LCR and NSFR. Growth in the size of banks' securities holdings coupled with changes in fixed income trading – such as reduced market making and more high frequency trading – may suggest that the collateral channel should receive greater attention in supervisory stress tests.

Having considered the four channels of stress, we present diagrams to use when considering potential bank responses to approaching regulatory ratio constraints. What can be observed from these schematics is that, in theory, banks always have options beyond deleveraging. But what these diagrams can help supervisors consider is whether assuming alternative options – such as the bank raising capital, extending the maturity of funding, or improving the bank's funding profile – is plausible given the stress scenario. It is worth noting that for all four ratios – RBC, LR, LCR and NSFR – deleveraging is a last resort for preventing a regulatory ratio breach, but the most important option from the point of view of potential systemic spillovers. Thus, a bank can end up facing an asset fire sale through any of the four risk channels, as well as due to any of the four Basel ratios becoming binding. This is relevant because while the channel of distressed selling has received extensive attention as a means of systemic risk propagation, less attention has been paid to the various paths instigating the fire sales.

Bank response after a shock

Graph 1



Extending the discussion of potential systemic risk transmission channels, Table 3 shows that if faced with no other option than to deleverage, a bank's deleveraging strategy can vary somewhat depending on which regulatory ratio is most binding. For example, when facing RBC as a constraint, a bank can sell non-zero risk weight securities – such as Level 2 assets – to obtain headroom as a first line of defence. By contrast, a bank cannot improve its leverage ratio through asset sales, as the cash counts equivalently in the denominator. Banks can only deleverage on-balance sheet assets to improve their leverage ratio if they can also retire outstanding liabilities, eg exercise a call option and use the cash to retire a bond or repay a repo transaction. Therefore, depending on its funding profile, it may be easier for a bank to shed off-balance sheet items – such as repos, derivatives and undisbursed loan commitments – if it seeks to achieve a quick improvement in its LR denominator. Interestingly, while the LCR and NSFR both encourage banks to hold substantial amounts of Level 1 HQLA, a bank's sale of

Level 1 assets would not improve either of these regulatory ratios, as Level 1 HQLA are marked to market and receive full credit akin to cash in both regulatory calculations. Thus, similar to a bank facing an RBC constraint, a liquidity-constrained firm would appear incentivised to first sell its non-Level 1 assets (which generally have higher risk weights), if forced to deleverage.

Hypothetical bank deleveraging strategy, by Basel regulatory ratio

Table 3

CAPITAL-BASED RATIOS		FUNDING-BASED RATIOS	
Risk-based capital ratio	Leverage ratio	Liquidity Coverage Ratio	Net Stable Funding Ratio
- Sell Level 2 assets - Cut interbank loans or reverse repos - Sell noncore assets - Do not roll over maturing loans	- Cut repos - Cut derivative positions - Cut commitments (selling assets does not help as cash counts in denominator).	- Sell Level 2 assets - Cut interbank loans or reverse repos - Reduce maturity of other loans	- Sell Level 2 assets - Sell non-HQLA or noncore assets

Source: OFR analysis.

In a similar vein, a recent paper by Pausch and Schmaltz (2013) offers a theoretical model that explicitly focuses on the interactions and feedback loops between an individual bank's liquidity and capital (and therefore the bank's solvency). The paper's formalisation of the effect of a liquidity reduction – either due to reduced inflows or higher outflows – on a bank's capital base via higher funding costs and/or fire sales of assets guides development of liquidity add-ons to micro-level stress tests for individual banks. Initial shocks, in this regard, comprise pure liquidity events as well as credit events which then may impact an individual bank's probability of default taking into account interactions between liquidity and solvency. This results in a broader assessment of bank stability at the micro level and identifies potential vulnerabilities through which external shocks (in the financial system) may take effect on the respective bank.

The latter information also links an individual bank to the financial system and provides a basis for macro stress tests. Macro-level transmission channels between liquidity and solvency – just like the bank lending channel,[7] the bank capital channel[8] and the risk-taking channel[9] – can then be better integrated into stress testing models. In addition to these more traditional well-known transmission channels, the suggestions of this paper explicitly take into account transmission channels that were of primary importance in the 2008–09 crisis. In particular, high leverage, maturity mismatches in banks' balance sheets, mark-to-market accounting and asset fire sales are considered for modelling relationships among banks and between banks and other players in the financial system.[10] From a technical perspective, network models are applied. These models consider specific links between banks as well as banks and non-bank (financial) institutions, and allow for analyses of when specific shocks spread out in the financial system.[11] The challenge in terms of network models, however, was to capture relationships via funding markets, markets for liquid assets held in a counterbalancing capacity and

7 See Bernanke and Blinder (1988).

8 See Bernanke (2007).

9 See Borio and Zhu (2008).

10 See, eg, Adrian and Shin (2010), Brunnermeier and Pedersen (2009) and Cifuentes et al (2005) for detailed representations of the more recent transmission channels.

11 See, eg, Upper (2011), Nier et al (2007), van Lelyveld and Liedorp (2006) and Boss et al (2006).

reputational effects, because existing models in the literature consider direct interbank relationships via repos, CPs, bank bonds and other bank liabilities. The paper, therefore, offers some ideas on how to include funding market contagion and asset fire sales in agent-based models.

3. Feedback from solvency to funding costs and funding access in supervisory stress tests

This section aims to present some straightforward ideas for supervisors interested in improving feedback from bank solvency to funding costs and short-term funding access in their supervisory stress tests. The first subsection (3.1) focuses on the empirics of the interaction between solvency and bank funding costs. It contains a short summary of the key empirical literature on bank funding costs and solvency interactions with an emphasis on what can be extracted for use in supervisory stress tests (3.1.1). This critical assessment of the literature provides the context for the original work presented in subsection 3.1.2. This subsection presents the results of a simultaneous equation panel model which aims to account for the endogeneity of funding costs and solvency positions of banks using a panel of international banks. In the next subsection (3.2), several work stream members present their use of a Merton model to estimate the ratings transition of banks during the supervisory stress test period. These estimates of banks' ratings migration can inform estimates of funding costs and funding run-off in stress and can provide an alternative market-based perspective on solvency.

3.1 The empirics of the interaction between bank solvency and funding costs[12]

3.1.1 A critical assessment of the empirical literature on the interaction between bank solvency and bank funding costs

This subsection provides an overview of the empirical literature on the interdependence of bank solvency and bank funding costs. It aims to frame the original empirical analysis of the issue presented in the next subsection (3.1.2) and to answer two questions: (i) Is the interaction between solvency and funding costs empirically significant?, and (ii) If so, how can it be calibrated in macroprudential stress tests? The key challenge in this literature centres on the fact that a bank's funding costs and its solvency position are determined jointly. For example, high funding costs can erode bank earnings, thus adversely impacting their solvency. Likewise, banks approaching insolvency may see their funding costs rise. When measuring the connection between solvency and funding costs, the literature has addressed this endogeneity problem in a number of ways.

Annaert et al (2010) study the determinants of credit default swap (CDS) spreads for 31 euro area banks from 2004 to late 2008. Their primary data source is Datastream. The explanatory variables are market-based financial leverage metrics such as weekly equity returns, historical stock return volatility, the risk-free rate, bank-specific CDS bid-ask spreads, the slope of the term structure of interest rates, and proxies for the general business climate and bank stability. Based on a multivariate panel estimation, the authors find that the interaction between solvency and funding costs is indeed significant – higher leverage increases bank funding costs. A 1 percentage point drop in weekly bank stock returns (associated with higher implied market-based leverage), is associated with a 64 bp rise in a bank's CDS spread.

[12] Drafted by S W Schmitz, M Sigmund and D Unterkofler (Central Bank of the Republic of Austria) and L Valderrama (International Monetary Fund).

Gray et al (2012) use a CCA approach to compute a fair value credit spread (FVCDS) as a proxy of bank funding costs. Their main data source is Moody's CreditEdge. Combining FVCDS with an implied market-based capital ratio, the analysis yields a non-linear relationship between funding costs and bank capital. This approach has been applied in a stress testing context where an FVCDS is estimated under a baseline and adverse scenario. The CCA results give an estimate of the total losses to bank creditors and the market-based capital shortfall of each bank under each macroeconomic scenario. Under the baseline scenario, banks' weighted average expected default frequency (EDF) rises steadily at an accumulated pace of 75% by the end of the stress testing period. This is mapped to an equivalent 75% rise in the FVCDS. Yet, under the adverse scenario, the projected accumulated increase of 150% in the EDF measure is linked to a rise in the FVCDS of over 200%, revealing a non-linear relationship between market-based solvencies and funding costs. In contrast to the RTF work stream's analysis, the fair value spread in this paper is an estimate of a bank's CDS spread, excluding liquidity premiums and any distortion from implicit government guarantees or issuer's risk, rather than a measure of banks' funding costs.

Babihuga and Spaltro (2014) use an international panel of banks' observed CDS spreads to consider potential shocks to banks' funding costs. Their dependent variable, banks' 5-year CDS spreads, is a proxy for marginal funding costs; their explanatory variables are balance sheet items (ie levels and changes of the total capital ratio and its composition) and macroeconomic variables (ie real GDP growth, short-term interest rates and the slope of the yield curve). They also include two crisis dummies – one to capture the effects of the liquidity disruptions in August 2007 and one for the euro area sovereign debt crisis – as well as a number of bank-specific and country-specific control variables. The authors estimate a panel error correction model with their proxy for marginal funding costs as an endogenous variable. They use publicly available data for 52 banks in 14 advanced economies from 2001–12. The primary data sources are Bloomberg and Datastream. The analysis shows that, in equilibrium, the interaction between bank solvency and funding costs is indeed statistically and economically significant. In the long run, a 1 percentage point increase in bank regulatory capital reduces funding costs by 26 bp, though this relationship is somewhat reversed in the short term, where an increase in bank capital is associated with rising bank funding costs two quarters ahead. The results also suggest that higher-quality capital is associated with lower bank funding costs.

Pierret (2014) uses fixed-effect panel vector autoregressive (VAR) regressions to model the nexus between banks' solvency and liquidity risk. The paper aims to model three endogenous variables: short-term debt as a proxy of liquidity risk exposure, short-term assets to capture bank liquidity risk bearing capacity, and solvency risk measured by the expected capital shortfall (SRISK)[13] under aggregate stress defined by Acharya et al (2010, 2012) and Brownlees and Engle (2015). The sample includes 49 US banks examined over Q1 2000 to Q1 2013. SNL Financials and the NYU Volatility Laboratory data set serve as the data sources. The main result suggests that the interaction is empirically relevant and asymmetrical: higher solvency risk limits the access of a bank to short-term funding, but a firm with more short-term debt has a higher risk of insolvency in a crisis.

Hasan et al (2014) use a sample of 161 global banks from 23 countries. Their primary data source is Bankscope. They regress banks' CDS spreads on leverage, equity return volatility and the risk-free rate. In addition, they include CAMELS indicators, which account for bank fundamentals such as capital adequacy, liquidity risk and asset quality. Few of these are available in Bankscope but are proxied by indicators that are. The authors apply a multivariate panel regression without accounting for the

[13] The SRISK measure is defined as the difference between the regulatory capital ratio applied to the expected value of assets in the event of a financial crisis and the expected market value of capital. The stress event is defined as a market event featuring a 40% drop in the market equity index. Generally, this methodology estimates firm-specific equity losses given a modest decline in market returns, and then extrapolates the results. Capital shortfalls are estimated based on the liabilities of the specific firms.

endogeneity of capital adequacy or their market-based leverage variable. The paper finds that solvency has an impact on bank funding costs. An increase of 1 percentage point (100 bp) in market-based leverage raises CDS spreads by an average of 101 bp over 2001–11. This effect is slightly more pronounced after 2007, when the sensitivity of the coefficient increases to 103 bp.

Aymanns et al (2015) use balance sheet data to examine the sensitivity of bank funding costs to solvency measures, drawing on two data sets: the FDIC call report data set covering 10,000 banks over the period 1993–2013, and SNL Financial data covering 2,700 banks from 80 countries over 2003–13. Two proxies of bank funding costs are constructed: the average funding cost and the interbank funding cost. The solvency measure is constructed by applying principal component analysis to a variety of measures of bank capital including Tier 1 capital, total regulatory capital and the leverage ratio. Linear panel estimation shows that solvency and funding costs are significantly related. The solvency measure is negatively related to both the average and wholesale funding cost; the coefficient is larger in magnitude for wholesale funding, pointing to the higher credit risk sensitivity of wholesale investors. A re-estimation of the model on a yearly basis suggests that the sensitivity of funding costs to bank capital is larger in bad times than in good times, making this interaction particularly relevant for stress testing purposes. Interestingly, the analysis shows that the relationship between funding costs and solvency is non-linear, with funding costs showing higher sensitivity when solvency levels are lower. The magnitude of the solvency effect is typically small, with a solvency shock of 5 percentage points leading to an average increase in interbank funding costs of about 0.2 percentage points over 1993–2013. However, this effect rises by 50% in 2007, when wholesale funding providers' sensitivity to solvency risk reached its peak.

Distinguin et al (2013) differs from the above papers in two important ways: it studies the interaction between solvency and funding volumes (rather than funding costs) and it explicitly accounts for the endogeneity between solvency and funding volumes. The analysis uses a data set (sourced from Bloomberg) consisting of 870 US and European publicly traded commercial banks from the period 2000–06. To proxy for solvency, the authors use regulatory capital ratios as the dependent variable. On the funding side, they focus on two quantity variables as dependent variables (the inverse of the NSFR and a so-called liquidity creation indicator that is basically a weighted sum of liquid and illiquid assets and liabilities in terms of total assets).

In the solvency equation, return on equity (ROE), the loan loss provision ratio (LLP), the log of total assets and the dividend payout ratio are the exogenous variables. In the liquidity equation, a market power variable, GDP growth, the central bank policy rate and the spread between the one-month interbank rate and the policy rate of the central bank are treated as exogenous. In the solvency equation, the coefficient of the liquidity indicator is negative for both variants of the indicator. This indicates that banks that exhibit higher liquidity transformation also have lower regulatory capital levels. In the liquidity equation, the coefficient for regulatory capital is also negative. Banks with lower capital ratios have higher measures of liquidity transformation. The model does not include measures of bank-specific funding costs.

The evidence in the literature suggests that (i) the interaction between solvency and funding costs is indeed statistically significant, and that (ii) it might be economically relevant, especially during periods of stress. There is, however, substantial variation in the impact across the literature, as the magnitude differs from about 26 bp lower funding costs per 1 percentage point increase in the capital ratio (Babihuga and Spaltro *(*2014)) to a roughly 1-to-1 relationship (Gray et al (2012), Hasan et al (2014)). Also, the above papers assume that solvency would be exogenous with respect to bank funding costs. This is unlikely to be true in practice, however, and the coefficients and test statistics are likely to be biased. Unfortunately, the direction of the bias is uncertain. Banks that are perceived by bondholders to be riskier might face higher CDS spreads and also maintain higher CT1 ratios; the bank management might, for example, increase its CT1 ratio to address the market's perceived risk. And if this perception is unobserved in the empirical analysis, then ordinary least squares (OLS) estimates are likely to understate the negative impact of funding costs on solvency. By contrast, OLS estimates can overstate this negative relationship if positive shocks to solvency, which are likely to lower CDS spreads, remain unobserved. In concrete terms, if markets expect a bank to become safer by increasing its CT1 ratio, then current CDS spreads might decline. But if this expectation is unobserved, then OLS estimates will overstate the negative relationship between solvency and funding costs.

To help address this endogeneity concern, we build on Distinguin et al (2013) although our approach differs, as we focus on funding costs rather than funding volumes and draw on higher-quality data. Econometrically, we use a simultaneous equation approach within a panel framework. The exercise builds on a unique data set consisting of reporting data shared across agencies from six countries with a total of 38 large banks included in the estimations. Due to the sensitivity of the data, strict confidentiality arrangements were in place. The data set is of higher quality than the publicly available sources in other international studies. Studies that work with publicly available data have to rely on proxies chosen from available data. Note that since not all of these banks are publicly traded, some of the models estimated below use a restricted sample.

3.1.2 Addressing endogeneity in the empirics of the interaction between solvency and funding costs: a simultaneous equation panel approach

In this subsection, work stream members aim to measure the relationship between solvency and funding costs. In principle, the conceptual integration of funding cost increases into the simulated profit path in macroprudential stress tests is straightforward. The empirical estimates here – which attempt to address endogeneity on account of the fact that funding costs and solvency are jointly determined – can provide a useful starting point for the calibration of the impact of solvency stress on bank funding costs in supervisory stress tests.

3.1.2.1 Data overview

The data consist of an unbalanced panel of 54 large banks from six countries covering the period Q4 2004–Q4 2013. With 33 banks, the US has a majority of the sample, which also includes six Austrian, six Canadian, six Dutch and three Nordic banks. The bank data were shared among the work stream members of the respective countries and went through careful data filtering and quality checks.

The dynamics of the solvency-funding cost interaction are complicated by the different frequencies of regulatory data for funding costs and solvency. The frequency of the former is usually much higher (up to daily) than of the latter (usually quarterly). The empirical analysis focuses on quarterly data. Another challenge for the analysis is posed by the choice of the proxies used to capture funding costs and solvency risk.

We approximate bank funding costs by using the 5-year senior single name CDS spread for each bank in the sample. This yields the dependent variable FVCDS_5y. The sample consists of large international banks, for which CDS liquidity is usually higher than for the average bank or non-financial corporation. Nevertheless, CDS market liquidity for specific banks in the sample might be limited (eg for some of the smaller European banks). This would be captured by the bank-specific fixed effects. Banks can refinance themselves in several different markets (ie deposits, wholesale funding or the bond market). But data for overall funding costs are very scarce; this would not only require data for the time-varying liability structure of each individual bank, but also for the average price the bank pays for each liability class.

Therefore, we focus on the marginal cost of long-term wholesale funding; using CDS spreads as a proxy of the cost of raising one extra unit of funding from the market for 5-year unsecured wholesale funding. Under stress, banks are often shut out of the unsecured interbank market. Short-term funding is then substituted by central bank funding, which limits the variation and information content of short-term funding costs as a proxy for banks' marginal funding costs. In order to calibrate the interaction between solvency and bank funding costs, the actual funding structure of the particular bank must be taken into account. In addition, the costs of other funding sources must be calibrated. The case studies discussed in BCBS (2013a,b) are useful sources. We also employ two measures of bank solvency. First, we measure bank solvency using banks' regulatory capital ratio, namely the CT1 ratio. Second, we rerun the estimation using a market-based measure of bank default probability over five years, namely the expected default frequency (EDF_5y) estimated by Moody's CreditEdge.[14]

We consider a wide range of bank-specific variables as potential determinants of bank solvency and funding costs. As a measure of asset quality, we use loan loss provisions (LLPs) as a percentage of total assets (LLPRatio). We are aware of the shortcomings of this proxy. Banks have some leeway in determining LLPs and can use it as a signalling device to the market, to accommodate regulators, to smooth earnings over time and for tax optimisation purposes. In addition, regulations and accounting rules have an impact on the level and timing of the recognition of changes in banks' capital adequacy.[15] This recognition is part of the rationale for considering, as an alternative to the supervisory solvency ratio, the EDF measure, which is more market-based. Net income as a percentage of total assets (NIRatio) serves as a proxy for the bank's internal recapitalisation capacity. In addition, these two variables play central roles in solvency stress tests. As such, their interactions with funding costs could provide useful insights for the calibration of the interaction between solvency and funding costs in stress tests. Finally, we measure bank liquidity risk using a simple stock approach. Short-term wholesale debt (liabilities with a remaining maturity of less than three months) is a proxy for liquidity risk exposure. Liquidity risk bearing capacity is defined as the stock of liquid assets (cash and central bank excess reserves, sovereign debt with risk weights of 0% and 20%). The variable LiRisk is defined as the ratio of the two at the end of each quarter. Finally, we take into account a bank's credit rating from S&P (S&P rating). We transform the standard rating scale into a 1 (best rating, or AAA) to 24 (worst rating) scale.

We address the potential regime shift around the outbreak of the global financial crisis in 2008 by using the following control variables: first, we include a non-bank, non-country specific variable that proxies for market sentiment in the short-term money market. The LIBOR-OIS spread is a widely used gauge for tensions in this market. It tends to be high in times of stress and low otherwise. We use the quarterly average (LIBOR_OIS). In our empirical analysis, it captures all events that have an impact on banks' solvency and funding situation, but are independent of bank and country characteristics. Second, we use a country-level indicator for sentiment in the local credit market (Loan_growth). High private sector credit growth can be associated with periods of high capital ratios as banks increase their CT1 ratios to fund loan growth.

The substantial changes seen in monetary policies and the introduction of unconventional measures could have an impact on bank funding costs. Although the specifics of unconventional measures differ between the various currency areas in our sample, we do not want to over-engineer the interaction between unconventional monetary policy and bank funding costs. The reliance of individual banks on these central bank measures might differ, but the information is not publicly available in a systematic manner. In the model, we allow for bank-specific fixed effects to capture such unobservable differences. We use the LIBOR-OIS spread as a proxy for the monetary policy stance at the global level.

14 Moody's model is a Merton-type model, as discussed later in Section 3. The main intuition behind the model is that the equity of a company is analogous to holding a call option on the company's assets, where the required debt payment at the horizon date serves as the option's strike price. The firm's CDS spread is not an input in the model. Regulatory capital may serve as a proxy for the effective capital ratio (ie the net worth), since the effective capital ratio might be lower than the regulatory capital ratio due to the fact that the regulatory capital ratio can include preferred shares, hybrid securities and other sorts of subordinated debt. However, the firm's effective capital ratio serves as a loss buffer. Therefore, the higher the effective capital ratio, everything else equal, the lower the probability of default. See Sun (2012) for further discussion of Moody's methodology.

15 See Report of the BCBS RTF TF on Regulation and Accounting ("The interplay of accounting and regulation and its impact on bank behaviour", BIS, forthcoming) for further details.

Global risk attitude can have an impact on bank funding costs; especially hedging products such as CDS spreads can increase with global risk aversion. We include a market measure of volatility to capture global risk aversion (VIX).[16] The market sentiment variables are only included in the bank funding cost equation. These variables directly affect funding costs, but not CT1 systemically (though an increase in the VIX could increase RWAs for banks with large equity portfolios). Over time, the indirect effects are captured in the simultaneous equation approach via funding costs. Finally, we add a crisis dummy (CrisesD) that captures significant changes in the interaction between funding costs and bank solvency as well as other explanatory variables. In particular, market expectations regarding bank capitalisation changed abruptly with Lehman's bankruptcy. The dummy variable is defined as 0 from Q4 2004 to Q3 2008 and as 1 from Q4 2008 to Q4 2013. Despite the control variables, it is possible that the interaction between solvency and funding costs changed over time; for example, we would expect wholesale investors to be more sensitive to solvency risk post-Lehman. Therefore, we also run our equations separately for two subsamples (pre- and post-Lehman default) to check for robustness.

Table C.1 in Appendix C shows data coverage for the variables used in the estimation, whereas Table C.2 presents the summary statistics. Note that most of the variables are denoted in percentage points. This also holds for FVCDS_5y. The median value stood at 1.31% (or 131 bp) across all banks over the entire period. The quartiles of the EDF_5y are: 0.08% (first), 0.3% (second) and 0.94% (third). In addition, Table C.3 provides a cross-correlation matrix of the dependent and independent variables used in the analysis. For further details about the bank data, see Appendix C.

3.1.2.2 Methodology: Simultaneous equation models

To address the fact that funding costs and solvency are jointly determined, especially when regulatory solvency indicators can be slow-moving compared to funding costs determined in wholesale funding markets, we use a simultaneous equation framework. The structural form of a simultaneous equation system reads as follows:

$$Y\Gamma = XB + U \quad (1)$$

In our analysis, Y is a vector of two endogenous variables (for example, solvency and funding costs), and X is a vector of exogenous variables including bank-specific variables (eg LLP ratio), country-specific variables (eg loan growth) and global variables (eg VIX and crisis dummy).

In terms of economic interpretation, it is helpful to look at one of the equations of the system in more detail:

$$y_{1,t} = y_{2,t}\gamma + x'_{1,t}\beta + u_{1,t} \quad (2)$$

$y_{1,t}$ is the first endogenous variable in the solvency equation (EDF_5y or CT1).

$y_{2,t}$ is the second endogenous variable in the funding cost equation (FVCDS_5y).

$x_{1,t}$ is the list of exogenous variables used in the first equation. These consist of bank-specific (eg loan loss provisioning ratio, LLPRatio, net income over total assets, NIRatio), country-specific (eg five-year senior government CDS, CDS_gov), loan growth to the private sector (loan_growth), and time-dependent global variables (eg a dummy crisis variable, CrisesD).

Rewriting equation (1) in reduced form simplifies the problem at hand:

$$Y = XB\Gamma^{-1} + U\Gamma^{-1} = X\Pi + V \quad (3)$$

[16] LIBOR-OIS captures very bank sector-specific disruptions in the short-term money market, while the VIX captures market volatility in US equity markets in which banks are but one sector among others.

Statistically, several conditions need to hold in order to extract the matrices Β and Γ from an estimated Π. This problem is known as the identification problem. If it is possible to deduce the structural parameters in equation (1) from the known reduced-form parameters in equation (3), then the model is identified.[17] Economically, identification can be addressed in the specification of the equations. If one applied the same exogenous variables to identify two or more endogenous variables, then the model would neither be statistically identified nor economically meaningful. The two most common estimation methods for equation (1) are two- and three-stage least squares.[18] The two-stage least squares (2SLS) procedure has two steps. For each structural equation (2) it regresses $y_{i,t}$ on $x_{i,t}$ to obtain $\overline{y}_{i,t}$ – the predicted value of $y_{i,t}$ based on the exogenous variation induced by $x_{i,t}$. In the second step, γ and β are obtained by an OLS estimation of $y_{i,ts}$ on $\overline{y}_{i,t}$ and $x_{i,t}$. The three-stage least squares (3SLS) procedure combines the two-stage least squares procedure with seemingly unrelated regressions (SUR), where the fact that the errors of each structural equation might be related is taken into account.

We apply the 3SLS within the panel estimator, unless the overidentification test (see below) suggests a preference for 2SLS.[19] We include bank-specific fixed effects to capture time-invariant bank characteristics that have an impact on bank solvency and bank funding costs but are not included in the data set, such as governance structures or business models. Time effects are captured by global variables. From the OLS models, we know that the biases are substantial and yield counter-intuitive results. But addressing the endogeneity and simultaneity biases requires the identification of good instrumental variables. This is a challenge, and our approach incorporates a trade-off between addressing the biases of the OLS approach and the potential weaknesses of the 3SLS/2SLS approach: larger standard errors than OLS estimators and, if instruments are weak, similar biases as in OLS and incorrect test statistics. The instruments, for example for the solvency equation, can be invalid if they exert an independent effect on funding costs apart from the solvency channel. All that said, the results below generally yield economically more intuitive results than the OLS models, and appear robust across specifications (including two different measures of solvency). Nevertheless, the results should be interpreted with these restrictions of the simultaneous equations approach in mind. Further research with a larger sample size and a broader set of potential independent variables would be useful.

3.1.2.3 *Estimation results*

To capture the contemporaneous realisations of bank solvency and bank funding costs which mutually influence each other, we estimate our equations in a simultaneous equation panel approach, as discussed above. For the purpose of stress testing, it is of particular importance to understand how a regulatory solvency measure interacts with funding costs. Table 4 summarises the results of the simultaneous panel estimation for the regulatory solvency measure CT1 and bank funding costs as measured by the FVCDS_5y. Then, we check the robustness of the results by replacing the regulatory ratio by the market-based measure of solvency EDF_5y (Table 6).

[17] See Greene (2000), Chapter 16 for more details.

[18] See Theil (1971) and Zellner and Theil (1962) for more details.

[19] The estimator is described in more detail in Baltagi (2005), Section 7.3.

Results for the panel estimation of the simultaneous equation system in bank solvency (CT1) and bank funding costs (FVCDS_5y)

Table 4

			Specification 1		Specification 2		Specification 3	
			CT1	FVCDS_5y	CT1	FVCDS_5y	CT1	FVCDS_5y
Endogenous variables		CT1		**-1.41**		**-1.13**		**-1.12**
		Std. Err.		***0.27***		***0.23***		***0.41***
		$P > \lvert z \rvert$		***0%***		***0%***		***1%***
		FVCDS_5y	**-0.31**		**-0.32**		-0.24	
		Std. Err.	***0.09***		***0.09***		*0.20*	
		$P > \lvert z \rvert$	***0%***		***0%***		*22%*	
		$signDCT1^2$						0.08
		Std. Err.						*0.07*
		$P > \lvert z \rvert$						*26%*
		$signDFVCDS\_5y^2$					**-0.42**	
		Std. Err.					***0.15***	
		$P > \lvert z \rvert$					***0%***	
Exogenous variables	Bank-specific	LLPRatio	**-1.61**		**-1.59**		**-4.58**	
		Std. Err.	***0.31***		***0.31***		***1.33***	
		$P > \lvert z \rvert$	***0%***		***0%***		***0%***	
		NIRatio	-0.14	**-0.55**	-0.14	**-0.56**	**-2.16**	**-0.58**
		Std. Err.	*0.16*	***0.14***	*0.16*	***0.14***	***0.82***	***0.24***
		$P > \lvert z \rvert$	*37%*	***0%***	*37%*	***0%***	***1%***	***2%***
		S&P Rating (lag 1)		**0.33**		**0.30**		**0.31**
		Std. Err.		***0.08***		***0.08***		***0.13***
		$P > \lvert z \rvert$		***0%***		***0%***		***2%***
		CapitalIncreaseD			0.08		0.57	
		Std. Err.			*0.27*		*0.64*	
		$P > \lvert z \rvert$			*77%*		*38%*	
	Country-specific	CDS_gov		**4.29**		**4.14**		**4.30**
		Std. Err.		***0.41***		***0.41***		***0.70***
		$P > \lvert z \rvert$		***0%***		***0%***		***0%***
		Loan_growth	0.01		0.01		-0.18	
		Std. Err.	*0.04*		*0.04*		*0.12*	
		$P > \lvert z \rvert$	*87%*		*89%*		*14%*	
	Time-specific (global)	LIBOR_OIS		**1.85**		**1.71**		**1.12**
		Std. Err.		***0.32***		***0.32***		***0.50***
		$P > \lvert z \rvert$		***0%***		***0.0%***		***3%***
		VIX		**-0.09**		**-0.06**		-0.04
		Std. Err.		***0.02***		***0.02***		*0.03*
		$P > \lvert z \rvert$		***0%***		***0%***		*21%*
		CrisesD	**3.23**	**3.82**	**3.26**	**2.97**	**2.27**	2.45
		Std. Err.	***0.16***	***0.86***	***0.17***	***0.78***	***0.54***	*1.30*
		$P > \lvert z \rvert$	***0%***	***0%***	***0%***	***0.0%***	***0%***	*6%*
		Bank FE	x	x	x	x	x	x
		adj R^2	0.98	0.82	0.98	0.83	0.98	0.83
		McElroy R^2	0.81		0.80		0.72	
		Obs	*782*	*782*	*772*	*772*	*772*	*772*

Coefficients that are significant at the 95% confidence interval are in bold and highlighted in grey. The variables OIS and LiRisk are not significant in any specification.

Source: Work stream calculations.

Table 4 shows the results across various specifications for solvency and funding costs. For each specification, the first column shows the results of the regulatory-based solvency equation (CT1). The second column presents the results of the funding cost equation (FVCDS_5y). To account for the endogeneity of CT1 and FVCDS_5y, we apply the 3SLS method as described in the previous section. We also perform an overidentification test (see Table 5). This indicates that for specifications 1 and 2 in Table 4, the 2SLS square estimate is preferable. Thus, the results in these columns are based on 2SLS. We use the following variables to explain only solvency (Table 4, specification 1, CT1): a bank's LLP ratio and country-level loan growth.

LLP ratios can be influenced by regulatory, tax, and/or profit-smoothing considerations. Regardless of the reason for LLPs, higher values reduce profits and the CT1 ratio (ceteris paribus). In contrast, the interaction of the LLP ratio and a bank's CDS spread within a quarter depends on the reason for the LLPs; eg tax optimisation increases profits and can reduce CDS spreads. But high LLP ratios that reflect low credit quality are likely to be associated with higher CDS spreads. The variable country-level loan growth is included as a macro control variable. If the market is growing, banks tend to increase capital to compete for market share and to protect their franchise value. The variation of country-level loan growth does not directly and systematically explain the variation of individual bank CDS spreads. High loan growth could be associated with low CDS spreads, if it is interpreted as a sign of strong market growth, solid macroeconomic fundamentals and sound profitability. It can also be associated with high CDS spreads, when it is interpreted as a sign of low credit standards, reckless lending and mispricing of risk.

The variable S&P rating and the market variables sovereign CDS (CDS_gov), LIBOR_OIS and VIX are included in the funding cost equation, but not in the solvency equation: the bank's ratings directly affect the pricing of its CDS, but not its CT1 capital or its RWA within a quarter.[20] CDS_gov, LIBOR_OIS and VIX are market indicators and systematically co-vary with the market prices for CDS; higher sovereign CDS spreads lead to higher bank CDS spreads, as the value/credibility of any expected guarantee is reduced. But they do not systematically affect banks' CT1 capital or RWAs (bonds of the local sovereign have a zero risk weight and are often held on hold-to-maturity portfolios). Tensions in money markets affect bank funding costs directly, and higher market volatility increases bank CDS spreads within one quarter. But these market prices do not directly influence the CT1 capital or RWA of individual banks. They do so indirectly via funding costs.

We perform a series of tests. First, we test, for each equation, whether the instruments are weak. As a rule of thumb, a value of the F-statistic above 10 indicates that our instruments are not weak.[21] Second, we perform the J-test for each equation to check for exogeneity of the instruments.[22] The Durbin- Wu-Hausman test clarifies whether our solvency and liquidity variables are really endogenous.[23] Finally, we run an overidentification test for the system of equations.[24] If the J-tests confirm exogeneity of the instruments for each equation, the system overidentification test is used to test the 3SLS null hypothesis of 3SLS versus the 2SLS alternative. The results are reported in Table 5.

Specification 1 is our baseline specification. It yields 782 observations from 38 banks. Bank funding costs (FVCDS_5y) are statistically and economically significantly associated with bank solvency (CT1). A 100 bp increase in a bank's CDS spread is associated with a 31 bp reduction in its CT1 ratio. This result is robust across specifications 1 and 2. LLPs are also significant; higher LLPs are negatively correlated with CT1. The crisis dummy is statistically significant, has the expected sign and an economically meaningful magnitude. Post-crisis CT1 ratios are on average about 323 bp higher than

20 Ratings take bank solvency into account eventually, but ratings change infrequently and often lag CT1 changes such that we assume that they are not simultaneously determined with solvency in each quarter.

21 Staiger and Stock (1997).

22 Bhargava (1991).

23 Nakamura and Nakamura (1981).

24 Wooldridge (2002), p 201.

before the crisis. The adjusted R^2 is very high, at 98%. The test for weak instruments fails to reject the hypothesis that the instruments are weak, if we include the contemporary S&P bank-specific rating in the funding cost equation. We therefore instrument for it by its lagged variable S&P Rating (lag 1). The test then rejects the hypothesis of weak instruments (see Table 5).

The CT1 ratio is statistically significant in the bank funding cost equation (FVCDS_5y). A 100 bp higher CT1 ratio is associated with a decrease of 141 bp in bank funding costs. This effect is robust in alternative specifications. In addition, stress scenarios impact net income, and the latter has a statistically and economically significant impact on bank funding costs as well. Country-specific government risk (CDS_gov) is statistically and economically significant. Also, the bank-specific rating (S&P Rating lag 1) has the expected sign and is statistically significant; tensions in the money market – as measured by the LIBOR-OIS spread (LIBOR_OIS_aq) – increase bank funding costs.[25] Global risk aversion (VIX) is significant, though with a negative sign which we attribute to the spikes in LIBOR_OIS when VIX also spiked during the heights of the crisis. The crisis dummy (crisesD) is statistically significant, too. The adjusted R^2 is 82% and sufficiently high to show that the equation does have some explanatory value for variations in bank funding costs. As an additional goodness-of-fit test, we provide the results for the McElroy R^2.[26] At 81%, it suggests that the explanatory value of the system is high.

In specification 2, we study whether taking into consideration deliberate management actions to improve bank solvency has any impact on the results. We construct a dummy variable (CapitalIncreaseD) from the CT1 variable. An increase in CT1 capital of more than 20% quarter on quarter in nominal terms serves as a proxy for deliberate management action.[27] This might stem from share issuance, asset sales or public support measures. In fact, the various public interventions in Q4 2008 seem to be well captured by this dummy. Capital increases directly affect CT1, but systematically co-vary with bank CDS spreads only via changes in CT1. It turns out that the variable CapitalIncreaseD is not statistically significant. The results for the endogenous variables and the other exogenous variables are basically unchanged. The reduction in firms' funding costs associated with higher capital ratios is -113 bp, somewhat less than in specification 1.

We then add the squared values of the endogenous variables to test for non-linearities (specification 3).[28] These variables ($signDCT1^2$ and $signDFVCDS\_5y^2$) are calculated as squared quarter-on-quarter first differences while maintaining the sign of the change. We treat these variables as additional endogenous variables in the estimations and include the fitted values of the underlying equations (not the observed values).[29] CT1 remains significant in the funding cost equation, but FVCDS_5y becomes insignificant. However, the coefficient of the squared quarter-on-quarter difference in funding costs is significant: the additional variables leave most other coefficients basically unaffected, but the LLP coefficient becomes quite high. An increase in funding costs is significantly associated with a decrease in CT1.

To help gauge the direction of the bias due to the joint determination of solvency and funding, we provide the OLS estimate of the coefficients of CT1 and FVCDS_5y in specification 1: the former is

[25] The variables that serve as instruments for the FVCDS_5y in the CT1 equation are significant in the funding cost equation. We conclude that, given our assumptions, the results do not reject their usefulness as instruments.

[26] The McElroy R^2 provides a goodness-of-fit measure for systems of equations (McElroy (1977)).

[27] This yields 70 observations for the dummy variable across all banks and quarters.

[28] However, we treat this approach as a first approximation, as accounting for non-linearities in linear models is not equivalent to constructing non-linear models of the underlying processes. At this stage, we are not aware of applications of systems of non-linear models in panel data econometrics in financial economics.

[29] Wooldridge (2002), p 235.

+0.20 (standard error = 0.04) and the latter is +0.13 (standard error = 0.03). The results suggest that higher funding costs are associated with higher CT1 ratios, and that higher CT1 ratios are associated with higher funding costs. This suggests that without fully controlling for the management's reaction to market perceptions of risk, OLS estimates can significantly understate the negative relationship between funding costs and solvency. In addition, we run the Durbin-Wu-Hausman test for the endogeneity of CT1 and FVCDS_5y (see Table 5).

Test results for the specifications of the simultaneous equation system in bank solvency (CT1) and bank funding costs (FVCDS_5y) in Table 4

Table 5

		Specification 1		Specification 2		Specification 3	
		CT1	FVCDS_5y	CT1	FVCDS_5y	CT1	FVCDS_5y
F-statistic	Quality of instruments	**1058.15**	**79.32**	**1020.27**	**78.46**	**1054.55**	**77.30**
P-value	J-test	**8%**	**71%**	**6%**	**75%**	**96%**	**86%**
	Durbin-Wu-Hausman test	**0%**	**0%**	**0%**	**0%**	**0%**	**0%**
	System overidentification test	**0%**		**0%**		42%	

F-statistics and P-value in bold if test do not reject specifications and estimation methods in Table 4. J-test: reject null (instruments are exogenous) if P-value < 5%. Durbin-Wu-Hausman test: reject null of "CT1 and FVCDS_5y are exogenous" if P-value < 5%. System overidentification test: reject null (prefer 3SLS over 2SLS) if P-value < 5%.

The tests statistics for the specifications in Table 4 are generally satisfactory (Table 5). The quality of instruments- test rejects the null of weak instruments in all equations. The J-test fails to reject the null of exogeneity of the instruments. The Durbin-Wu-Hausman test is consistent with the endogeneity of the dependent variables. The system overidentification test for the 3SLS method (reported in Table 5) suggests a preference for 2SLS over 3SLS for specifications 1 and 2. For these, we report the 2SLS results in Table 5.

Results for the panel estimation of the simultaneous equation system in bank solvency (EDF_5y) and bank funding costs (FVCDS_5y)

Table 6

			Specification 1		Specification 2		Specification 3	
			EDF_5y	FVCDS_5y	EDF_5y	FVCDS_5y	EDF_5y	FVCDS_5y
Endogenous variables		EDF_5y		**1.40**		**1.35**		**1.37**
		Std. Err.		***0.12***		***0.14***		***0.18***
		P > |z|		***0%***		***0%***		***0%***
		FVCDS_5y	**0.66**		**0.59**		***0.61***	
		Std. Err.	***0.05***		***0.05***		***0.05***	
		P > |z|	***0%***		***0.0%***		***0%***	
		signDEDF_5y²						0.05
		Std. Err.						*0.03*
		P > |z|						*6%*
		signDFVCDS_5y²					-0.03	
		Std. Err.					*0.03*	
		P > |z|					*29%*	
Exogenous variables	Bank-specific	LLPRatio	0.08		0.19		0.12	
		Std. Err.	*0.12*		*0.12*		*0.29*	
		P > |z|	*52.8%*		*12.7%*		*69%*	
		NIRatio	-0.11	0.12	-0.12	0.07	-0.22	0.24
		Std. Err.	*0.07*	*0.11*	*0.07*	*0.13*	*0.16*	*0.18*
		P > |z|	*11.3%*	*27.8%*	*10.3%*	*59.0%*	*16%*	*17%*
		S&P Rating		0.02		0.09		0.09
		Std. Err.		*0.03*		*0.04*		*0.07*
		P > |z|		*48.1%*		*5.4%*		*15%*
		CapitalIncreaseD			0.00		0.03	
		Std. Err.			*0.04*		*0.05*	
		P > |z|			*89.7%*		*53%*	
	Country-specific	CDS_gov		0.18		0.63		0.35
		Std. Err.		*0.27*		*0.36*		*0.52*
		P > |z|		*49.9%*		*7.8%*		*50%*
		Loan_growth	-0.01		-0.02		-0.01	
		Std. Err.	*0.01*		*0.01*		*0.02*	
		P > |z|	*47.2%*		*6.9%*		*64.1%*	
	Time-specific (global)	LIBOR_OIS	**-1.84**	**2.68**	**-1.80**	**2.68**	**-1.83**	**2.71**
		Std. Err.	***0.13***	***0.22***	***0.14***	***0.27***	***0.15***	***0.33***
		P > |z|	***0%***	***0%***	***0%***	***0%***	***0%***	***0%***
		VIX	**0.05**	**-0.08**	**0.06**	**-0.07**	**0.06**	**-0.08**
		Std. Err.	***0.01***	**0.01**	***0.01***	**0.01**	***0.01***	***0.02***
		P > |z|	***0%***	***0%***	***0%***	***0%***	***0%***	***0%***
		CrisesD	**-0.26**	**0.36**	-0.06	-0.09	-0.12	-0.02
		Std. Err.	***0.08***	***0.12***	*0.10*	*0.19*	*0.12*	*2.31*
		P > |z|	***0.1%***	***0.2%***	*52.8%*	*63.5%*	*34.6%*	*94%*
		Bank FE	*x*	*x*	*x*	*x*	x	x
		adj R²	0.67	0.83	0.67	0.83	0.67	0.84
		McElroy R²	1		0.99		0.55	
		Obs	946	946	773	773	771	771

Coefficients that are significant at the 95% confidence interval are in bold and highlighted in grey.

Source: Work stream calculations.

Table 6 shows the results of the analysis using the market-based EDF measure as a proxy of bank solvency. We run this as a robustness check, based on the same specifications, though for stress testing purposes the results are of less relevance than those for regulatory solvency measures. In specification 1, the analysis is based on 946 observations for 38 banks in six countries from Q4 2004 to Q4 2013. The test for weak instruments suggests that the instruments of the same specifications as in

Table 4 are weak. LIBOR_OIS and VIX are market indicators. It is less plausible that they do not co-vary directly with the market measure for solvency than it is for the regulatory solvency measure. We therefore also include the two in the solvency equations in Table 6. The results show that the impact of bank funding costs on the market measure of solvency is statistically and economically significant – a 100 bp increase in FVCDS_5y is associated with an average increase of 66 bp in the EDF. The bank-specific variable LLPRatio and the country-specific variable loan growth are not statistically and economically significant. As suggested by the test for weak instruments, the market indicators LIBOR_OIS and VIX are significant in the solvency equations, too. The VIX now has the expected sign, but the LIBOR_OIS spread influences solvency negatively through funding costs. Once this is controlled for, it decreases the EDF. The crisis dummy (CrisesD) is statistically significant, but has an unexpected sign. After controlling for higher funding costs, money market conditions and general risk aversion, EDF_5y is generally somewhat lower post- than pre-Lehman. The R^2 is relatively high, at 67%.

The association between the market measure of solvency and funding costs is positive and highly significant at the 1% level: the coefficient 1.40 is economically significant. A money market shock – as measured by a spike in the LIBOR-OIS spread – translates into an increase in bank funding costs. Global risk aversion (VIX) reduces bank funding costs. While the coefficient is statistically significant, it has the wrong sign. We attribute this to the spikes in LIBOR_OIS when VIX also spiked during the heights of the crisis (Appendix C, Table C.3). Changes in government CDS (CDS_gov) do not directly affect bank funding costs. Finally, the crisis dummy (CrisesD) is significant: after Lehman, funding costs are generally higher. The R^2 is high with 83%. The McElroy R^2 is very high, at 100%, which suggests that the specifications including market-based measures of both solvency and liquidity are less relevant than the specifications including the regulatory solvency measure CT1.

In specification 2, we study whether taking into consideration deliberate management action that aims at improving bank solvency (CapitalIncreaseD) has an impact on the results. It turns out that the variable CapitalIncreaseD is not statistically significant. The coefficients and standard errors of the other exogenous variables LIBOR_OIS and VIX remain largely unaffected. However, the crisis dummy is not statistically significant anymore. In addition, the coefficients and standard errors of the endogenous variables are basically unchanged.

Again, we then add the squared changes of the endogenous variables in the current quarter to test for non-linearities (specification 3). The variables (signDEDF_5y² and signDFVCDS_5y²) are calculated as in the specifications in Table 4. Neither of them is significant; the coefficients of the other endogenous variables remain statistically and economically significant, with very similar coefficients. The same holds true for the coefficients of the exogenous variables.

Test results for the specifications of the simultaneous equation system in bank solvency (EDF_5y) and bank funding costs (FVCDS_5y) in Table 6 — Table 7

		Specification 1		Specification 2		Specification 3	
		EDF_5y	FVCDS_5y	EDF_5y	FVCDS_5y	EDF_5y	FVCDS_5y
F-statistic	Quality of instruments	**41.38**	**97.37**	**33.81**	**83.95**	**33.22**	**83.00**
P-value	J-test	**96%**	**66%**	**88%**	**69%**	**100%**	**95%**
	Durbin-Wu-Hausman test	**7%**	**0%**	80%	**0%**	83%	**1%**
	System overidentification test	41%		26%		95%	

F-statistics and P-value in bold if test does not reject specifications and estimation methods in Table 6. J-test: Reject null (instruments are exogenous) if P-value < 5%. Durbin-Wu-Hausman test: Reject null of "CT1 and FVCDS_5y are exogenous" if P-value < 5%. System overidentification test: Reject null (prefer 3SLS over 2SLS) if P-value < 5%.

The tests statistics for the specifications in Table 6 are generally satisfactory (Table 7). The quality of instruments test rejects the null of weak instruments in all equations. The J-test fails to reject the null of exogeneity of the instruments. The Durbin-Wu-Hausman test for the solvency equation is only significant at the 7% level in specification 1 and insignificant for the other specifications. It suggests that endogeneity is less of an issue for the market-based solvency measure. The system overidentification test is satisfactory for 3SLS.

To sum up, the results summarised in Table 4 and Table 6 provide a number of insights relevant to supervisory stress tests:

The endogeneity and the simultaneity biases in OLS models of solvency and funding costs are large, and yield results that are counter-intuitive. While the 3SLS approach has its own challenges and while our results should be interpreted with these methodological restrictions in mind, the results suggest that regulatory solvency ratios and bank funding costs are not independent, but determined simultaneously. Compared to the literature reviewed in Section 3.1.1, our results suggest a larger impact from solvency on funding costs. This result also holds for the interaction between market-based solvency measures and funding costs. More generally, the evidence suggests that the outcomes of supervisory stress test models which incorporate solvency and funding cost interaction, as discussed in Section 4, are indeed relevant. These interactions are not artefacts of the modelling assumptions employed, but appear to reflect important dynamics. Stress test models that do not take into account the interaction between solvency and funding costs are likely to underestimate the impact of stress on banks' solvency and financial stability.[30] Also, the estimated coefficients of net income and the CT1 ratio in the funding cost equation can be used as starting points to parameterise the implications of solvency stress on bank funding costs in stress tests.[31] Net income and CT1 ratios are core variables which are routinely determined in solvency stress tests for every quarter. Based on our results, their effects on bank funding costs can be parameterised to model the feedback effect on bank solvency in the stress test.[32] While the results are encouraging, it would be desirable to confirm the robustness of these results with a broader sample of banks, longer time series and a broader set of countries.

3.2 Micro-interactions between funding and solvency: insights from Merton models[33]

Traditional supervisory stress tests focus on solvency as measured by regulatory capital ratios. However, regulatory capital ratios are only one factor determining the risk of insolvency and also may not prove fruitful in evaluating the risk to firms of liquidity stress. Alternative assessments of the output from stress tests are therefore warranted.

30 At the same time, distress might be predicted more accurately by downplaying the role of capital in reducing CDS spreads. The forecast implicitly accounts for the possibility that banks with higher capital ratios hold riskier assets.

31 Based on the results for the 5-year CDS spread, the costs of other funding sources must be calibrated and the funding structure of the bank taken into account. The case studies discussed in BCBS (2013a,b) are useful sources.

32 Consider the following mechanical example [In this simple example, we assume that all other funding costs of the bank (eg deposits) do not change and that the bank has a funding structure similar to the average of the banks in our sample.]: On average, the solvency stress test under an adverse scenario reveals a reduction in net income (in bp of total assets) from 15 bp (of total assets) to 0 bp, and a drop in the CT1 ratio from 6.1% of RWA to 5.8% (due to an increase in RWA) in the first quarter. On average, this would translate into a contemporaneous increase in the bank's (marginal wholesale) funding cost of 51 bp ([-15 bp] × [-0.55] + [-30 bp] × [-1.41]) in the first quarter, ceteris paribus; which in turn would feed into the stress test as an idiosyncratic funding shock in the following quarter. While this might not seem spectacular at first sight, the quarterly interaction may add up over the time period of the stress test for two reasons: (i) the funding cost impact increases cumulatively over time, as net income and capital deteriorate further; (ii) depending on the maturity structure of the bank's cash flows, the amount of liabilities which need to be refinanced increases over time; this increases the cost and solvency impact. In the example, we use the coefficients across the entire sample rather than those of the post-Lehman fallout, because not every stress scenario necessarily involves a crisis of this scale.

33 Drafted by K Anand (Bank of Canada), J Cetina (Office of Financial Research) and H Solheim (Central Bank of Norway).

One such option is to apply a contingent claims analysis (CCA), more commonly known as a Merton model.[34] For example, the IMF in the context of its Financial Sector Assessment Program (FSAP) sometimes includes a CCA as part of its top-down stress test (see Jobst and Gray (2013)). There are also a number of commercial Merton models available. Work stream members considered whether a Merton-type analysis could strengthen bottom-up stress tests. Specifically, several work stream members tried using a Merton-type model to estimate the implied credit ratings of banks under supervisors' stress scenarios.

Credit ratings could provide a better indication of funding costs and funding availability than regulatory capital ratios and, depending on the amount of implied ratings transition, provide a market-based alternative perspective on banks' solvency that could offer useful and complementary insights relative to regulatory capital ratios. As will be discussed, a good implied default probability/credit rating model will take into account other parts of the information set than what is traditionally emphasised in a supervisory stress test. However, it does require some parameters not currently collected in most supervisory stress tests.

3.2.1 Model overview

Merton models provide one way to estimate probabilities of default and rating transitions for publicly traded banks under stress. A Merton model evaluates the credit risk of a firm's debt by looking at a put option on the firm's equity.[35] Merton models are often used to predict default probabilities, and the results can be used to estimate an implied rating. While supervisors ideally may prefer the models they use to be developed in-house, there are a number of off-the-shelf commercial models of default estimation based on Merton-like approaches (for example, see Bloomberg's DRSK function, Moody's CreditEdge and Kamakura) that can be used to evaluate banks. A potential benefit of using a mainstream commercial model as opposed to an in-house model is that such a model might be used by banks and other non-bank financial counterparties to evaluate a bank's credit risk.

To look at the potential insights from these kinds of models, three work stream members (Canada, Norway and the United States) used data for individual banks from their national supervisory stress tests with Bloomberg's DRSK module. The DRSK function has the advantage that it is integrated in the software on the Bloomberg terminal and therefore already available to most regulators.[36] This function is a Merton-type model, and will calculate an implied default probability and implied rating. The model will also provide an estimate of the funding cost, measured as implied CDS spread, associated with each estimated rating. The model estimates implied default rates, implied ratings and implied CDS spreads based on current data, but it is closed form and thus also allows the user to alter the main model inputs and return implied ratings and CDS spreads for alternative assumptions which could be drawn from supervisory stress test scenarios. The work stream members estimated individual banks'

[34] The name reflects the model's roots in options pricing theory pioneered by Black and Scholes (1973) and Merton (1973, 1974).

[35] The Merton approach assumes a firm is solvent as long as the value of its assets is greater than its liabilities. However, the value of assets is unobservable so the model uses the market capitalisation to impute the value of assets. The key insight of a Merton-type framework is that the equity of the firm can be viewed as a call option on the total assets of the firm, where the strike price is equal to its liabilities. As with all options pricing models, realised share price volatility is also a key parameter in a Merton model.

[36] In a forthcoming paper, Cetina and Loudis ("The influence of systemic importance indicators on banks' CDS spreads", *Journal of Risk Management in Financial Institutions*, December 2015) find using a GLS model, that in a horse race of vendor models, the DRSK model does the best job in explaining an international sample of banks' observed 5-year CDS spreads between 2010 and 2014.

implied rating transitions using selected bank-level outputs from the worst period in their national supervisory stress tests.

The Bloomberg DRSK model uses eight input variables to estimate implied default probabilities: share price, market capitalisation, share price volatility, short-term debt, long-term debt, loan-loss reserves, non-performing loans and net income.

All three work stream members used worst-case stress test values for loan loss reserves, net income and non-performing loans for individual firms. Otherwise, the three work stream members took alternative approaches to estimating the other inputs.

Summary of Merton model application to supervisory stress tests — Table 8

Country	Stress test scenario	Approach to estimating share price	Bank level output	Stress testing takeaways
Canada	Bank of Canada's 2014 FSR	Use stress test assumption for decline in Canadian bourse but use bank-specific volatility assumptions based on credit losses	Implied ratings for all six domestic systemically important banks fell several notches from investment grade to sub-investment grade	From a regulatory capital perspective, MFRAF suggest that banks have adequate cushions to withstand adverse credit shocks and runs. However, from a market perspective, the Merton model suggests that banks will be severely impaired.
Norway	Modified version of FSR 2013	Estimate beta for individual bank share prices and use this in combination with stress test-assumed decline in Norwegian bourse	Two of six banks declined to sub-investment grade	Banks that do well in terms of regulatory requirements might still be punished in the funding market, due to combination of share price fall and weak initial CDS spread
United States	DFAST 2013	Reverse stress test – what share price assumption needed to trigger downgrade to sub-investment grade	20–84% share price decline needed for individual banks to cross investment grade threshold	Insights from Merton analysis different from those suggested by risk-based capital. Banks that DRSK suggests are most at risk for sub-investment grade rating transition under supervisory stress scenario did not assume any short-term funding run-off in their stress test submissions.

3.2.2 Discussion of use to complement supervisory stress test data

The work stream member from Canada used the Merton model in conjunction with the Bank of Canada's top-down stress test suite of models, MFRAF, to estimate the implied probability of default for the six Canadian domestic systemically important banks. The decline in share prices and volatility were calibrated to a stress scenario described in the Bank of Canada's 2014 *Financial System Review* as a key risk to the Canadian financial system (cf Anand et al (2014)). The materialisation of this risk prescribed – in the worst case – a 39% decline in the S&P/TSX Composite Index and a 51% increase in the implied volatility.

Banks' non-performing loans were calculated as expected losses, with the probabilities of default across the different economic sectors estimated econometrically. Assumptions of the loss-given-default rates were made to be consistent with past stress test exercises. Finally, banks' net incomes were calculated using two auxiliary models that forecast net interest margins and non-interest non-trading incomes. Additional parameters were taken from Bloomberg.

The stress scenario considered was severe, with the implied ratings for all banks falling several notches from investment grade to sub-investment grade. Concurrently, the estimated 5-year CDS spreads increased by an average of 180 bp, with very little variation across banks.

To better understand the uniformity in outcomes, a sensitivity analysis was devised wherein the share price volatility for each bank was made proportional to the bank's non-performing loans. The greater are the estimates for non-performing loans, the higher is the share price volatility. However, this had a very limited impact – both on the implied rating change and on the increase in the 5-year CDS spreads. The analysis thus suggests that a key driver of the results is the pre-crisis 5-year CDS spreads, which were also similar across banks.

The results from the Merton model shed additional light on the fragility of banks not captured by MFRAF. From a regulatory capital perspective, the results from MFRAF suggest that banks have adequate income generation capacity and cushions to withstand adverse credit shocks and runs. However, from a market perspective, the Merton model suggests that banks' funding (both secured and unsecured) will be heavily stressed, which may affect financial stability.

Another work stream member, Norway, started with a severe stress scenario of the Norwegian economy. The shock was primarily centred on losses in the corporate sector. Loan loss reserves, non-performing loans and net income were collected from the stress test output. The ratio between short-term and long-term debt was assumed to be constant, although it would probably be more realistic to assume an increase in the share of short term-debt in the stress scenario.

The institution's share price is an important input in this kind of model, but such prices are not standard output from the supervisory stress test. In the stress scenario, the Norwegian composite index, OSX, was assumed to fall 30%. The work stream member made a simple model to fit the individual banks' share prices to the stress scenario. The approach was to assume a relationship between the share price and the difference in actual return on equity from the target return on equity. In the model, the target return on equity in equilibrium was 12% (a historical average), but this will fall in stress as one allows a transition period from the current return back to the 12% level. The share price was assumed to stay constant if the actual return equalled the target return, and to fall 50% if the actual return was zero.

In line with historical observations, share price volatility was set to increase with a fall in the share price. So, for example, a 50% fall in the share price doubled the volatility. This made the stress scenario comparable to the 2008 experience. Market capitalisation was assumed to change with the changes in the share price.

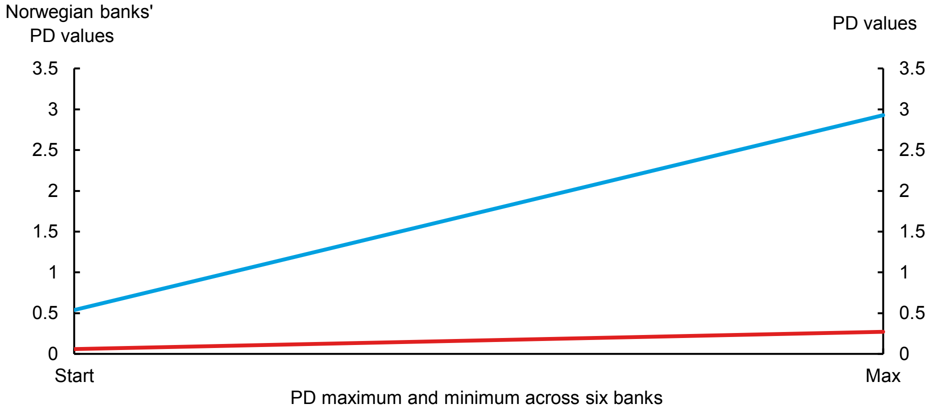
All six Norwegian banks started with an investment grade rating. Four banks with a high share of household lending retained positive net profits and stable capital ratios in stress, while two banks with more corporate exposure experienced zero net profits and a fall in capital ratios. All banks remained well in excess of minimum capital requirements. The maximum estimated fall in the share price for the six banks in the stress scenario was between 20 and 50%. The decline in the share price for the bank hardest hit was in line with what we observed during the autumn of 2008.

According to the DRSK model, two of the six banks' implied ratings would decline below investment grade in the stress scenario. The bank with the highest and the bank with the smallest drop in share price were downgraded to sub-investment grade, while the rest of the banks transitioned among investment grade ratings but remained at investment grade. The bank with the smallest fall in share price was downgraded despite positive net profits throughout the stress scenario. Testing for the sensitivity of the results to the assumptions of share price volatility, it was found that the volatility assumption almost doubled the implied default probability for the bank with the largest fall in share price compared to leaving the volatility at the 2014 level.

Notably, the initial implied rating was very important for the predictions in the DRSK model. The Norwegian banks had a more heterogeneous starting point than the Canadian banks. The percentage increase in the estimated default probability relative to the initial implied default probability was almost constant across banks that had the same fall in share price. Hence, if the starting point was different, there could be a substantial difference in the change when measured in the more relevant form of percentage points. Bank 1 had an initial implied default probability of 0.05%, while bank 2 had 0.5%. At the end of the stress period, the default probability of bank 1 had increased to 0.25%, while bank 2 was at 2.5%. Bank 1 remained investment grade and bank 2 was downgraded. The effects on the distribution are indicated in Graph 2.

Max-min PD values

Graph 2



Last observation: max stress value

Source: Central Bank of Norway.

The results highlighted that the effect of a shock is a factor of the initial position and of how hard the shock hits, ie the combination of vulnerability and realisation of risk. According to the DRSK model, even relatively small differences in initial implied default ratings are magnified in a crisis. Vulnerable banks experiencing small shocks to solvency can be hit harder in the funding market than less vulnerable banks hit by much larger solvency shocks. This might well be a reasonable assumption, and it is certainly a possibility the regulator should monitor closely.

A third work stream member from the United States used stress test data across reporting bank charters for seven large US bank holding companies. The results for net income and non-performing loans were summed up to simulate consolidated numbers for the parent entity. Bank holding company stress test data would be preferable to work with but were not available.

The work stream member ran the worst quarter of stress test losses and the non-performing loans associated with that quarter's stress test result through DRSK. For simplicity, the analysis instead focused on determining the necessary decline in individual bank holding companies' share prices under which the model would suggest a bank's rating would transition to sub-investment grade.

The exercise found that for these seven bank holding companies, the share price decline needed to trigger a sub-investment rating in DRSK ranged from 20–84%. As highlighted in the Norwegian experience, initial implied ratings (or estimated default probabilities), unsurprisingly, were generally a good predictor of the severity of the share price shock that would trigger a bank holding company's sub-investment grade rating transition. By contrast, banks' actual initial ratings were *not* good predictors of the sensitivity of individual firms to sub-investment grade transitions, as some banks with lower actual ratings required materially higher share price declines to trigger a sub-investment grade rating transition than some of their higher-rated peers. However, this result was not solely the result of differences between implied and actual ratings. For example, for two firms with comparable initial actual and implied credit ratings, the extent of share price decline the model estimated as necessary to trigger a sub-investment grade transition was quite different. For one firm, a 30% share price decline was sufficient to trigger a sub-investment grade transition, while for the other a 64% share price decline was required. This difference was likely driven by substantial differences in the firms' estimated losses to net income in the stress scenario.

Firms that the DRSK model suggested were most at risk of a sub-investment grade rating transition in the severe scenario also had some of the highest shares of short-term funding. These firms' stress test submissions did not assume any short-term funding run-off in the scenario even though the DRSK model suggested that the credit shock coupled with a 20–30% share price decline – minor in the context of the decline of around 80% that the US KBW bank equity index experienced between January 2007 and early 2009 – could materially affect market perceptions of the firms' credit standing and willingness to roll over wholesale funding.

3.2.3 Conclusion

This exercise highlights that supervisors should consider alternatives to modelling the effects on funding costs solely as a function of regulatory capital ratios. Market-based solvency measures and implied ratings may shed light on potential risks with respect to funding stress. It may be illuminating for supervisors to ask reporting banks to provide their own estimates for their share price and credit rating migration under stress scenarios. These estimates could then be used as described in this section to evaluate whether changes in funding costs or funding availability for a given bank would be appropriate. Market indicators for large banks, such as the estimated transition to a sub-investment grade rating under the stress scenario, might also be considered as triggers for forced deleveraging and asset fire sales in supervisory stress tests which result in second-round effects on other banks.

4. Overview of macroprudential elements in existing supervisory stress test models[37]

4.1 Discussion of supervisory models with liquidity and solvency interactions and/or systemic risk add-ons

As discussed in BCBS (2013), a range of top-down stress testing models has been developed by central banks over the last decade, gradually evolving to (i) fully fledged macro stress tests with the explicit aim of establishing macrofinancial linkages, ie to assess the resilience of financial systems under specific macroeconomic scenarios, and (ii) integrated frameworks to model dynamic and systemic effects. A limited set of supervisory stress testing models now include liquidity risk and feedback effects within the financial sector and – hence – systemic liquidity effects. The most advanced liquidity stress testing models are part of integrated frameworks that combine modules for credit, market and liquidity risk. Appendix A provides more details on these stress testing models of individual bank supervisors covered by the work stream.

In integrated stress testing models, scenarios are usually constructed as simulated shocks to bank credit portfolios that spill over into market and funding risk. The main characteristics of the models are summarised in Table 9. The models are applied to the local banking sector and based on bank level data, usually taken from supervisory sources. Most models use data on banks' stocks of liquid assets, based on balance sheet data and ratios. While the capital ratio usually functions as a trigger for second-round effects, the liquidity ratio – for instance, a liquidity buffer ratio like the LCR or spikes in funding

[37] Drafted by J W van den End (Netherlands Bank).

costs – are used to measure the stress level that results from those effects. Some models, like that of Netherlands Bank (DNB), also use cash flows, which provides for a richer time dimension of the data and enables a bucket analysis.

The assumed origin of the stress is usually an adverse shock to the credit portfolios of banks, which affects the risk drivers (PDs, LGDs) and/or asset values. These first-round shocks reduce the capital ratio. If capital becomes a binding constraint, liquidity risk emerges in various forms in most models. A declining capital ratio can lead to higher funding costs, charged by lenders as a reflection of higher counterparty risk. Liquidity risk can also follow from feedback effects arising from various transmission channels. Some models assume that funding rollover stops in response to higher counterparty risk and defaults in the network of exposures. This is a prominent feature in the Bank of Canada (BoC) model.

In most modelling approaches, the interaction between solvency and liquidity risk is a driving force behind the feedback effects. Shocks to the solvency position of banks and lower collateral values translate into reduced market access, liquidity hoarding and/or liquidity run-offs. These mechanisms are driving forces in the models of the Bank of Korea (BoK) and the Central Bank of the Republic of Austria (OeNB), among others. In some of these models, this triggers fire sales of assets, which further reduces asset values, creating feedback loops to the solvency position of the asset holders. Fire sales and liquidity runs are important mechanisms causing stress and contagion across the financial system. The interbank network – which is included in most models (see, for instance, the Bank of Mexico (BdM) model) – is a common vehicle for such effects.

In the stress testing models, systemic risk arises as a result of bank behaviour. Some models explicitly define reaction rules, which range from rather static rule of thumb triggers to dynamic approaches in which banks optimise their balance sheet based on risk/return trade-offs. The latter is a prominent feature of the ECB model. In some models, the liquidity effects of bank reactions affect the solvency position of other banks, as part of a wider feedback loop. Such loops can run via financial markets (through asset fire sales) or via the real economy, if banks react to the shocks by adjusting their lending rates or volumes. This may undermine the credit risk of banks' borrowers and so create feedback to banks' loan books, as in the Central Bank of Norway (CBoN) model.

Key points from selected supervisory stress tests with liquidity and solvency interactions and/or feedback effects

Table 9

	BoC	OeNB	DNB	BdM	BoK	CBoN	ECB
Data	Balance sheets, cash flows, interbank exposures from supervisory sources and bottom-up stress tests	Prudential reporting data, data from credit register	Supervisory data, stocks and cash flows	Detailed information on individual banks	Detailed supervisory information on balance sheets	Quarterly banking data, public data source	Detailed data on EU and EA banks
Type of shocks	Macroeconomic shocks to credit risk	Macro shocks affect credit risk, haircuts and counterbalancing capacity	Valuation losses and/or funding withdrawals to selected liquidity items	Joint credit and market losses due to macroeconomic shocks	Macro shocks affect solvency risk	PD, LGD shocks	Market, credit and interest rate shocks
Feedback mechanisms	Rollover stops on maturing claims, exacerbated by valuation losses on assets	Solvency stress reduces cash inflows, access to the unsecured interbank market, commercial papers and bond markets; value of unencumbered collateral deposited at the central bank drops; liquidity stress feeds back into solvency stress test	Responses by banks to restore liquidity ratios, feedback on asset values and funding availability	No, static model	Interbank default, AFS and deleveraging leads to losses	Feedback from lending rate and capital ratio to macro model	Feedback to real economy using DSGE and reduced form models

Key points from selected supervisory stress tests with liquidity and solvency interactions and/or feedback effects | Table 9

	BoC	OeNB	DNB	BdM	BoK	CBoN	ECB
Solvency / liquidity interaction	Expectations of insolvency determine rollover risk, capital shortfalls amplify interbank contagion	Funding cost shock and AFS losses feed into solvency stress tests via P&L	Valuation losses influenced by AFS and central bank interventions, link from liquidity risk to credit supply	No, credit and liquidity risk not integrated	Decrease in capital ratio triggers liquidity run-off	Funding costs determining factor of lending rate and capital management	Funding costs impact on solvency collateral values, capital injections influence
Balance sheet dynamics	Not behaviourally driven	Asset sales to balance loss of funding (Counterbalancing capacity); calibration based on empirical literature on asset fire sales	Driven by bank responses to restore liquidity ratio	No, static model	Banks hoard liquidity in response to shock	Optimising bank behaviour with regards to lending rate driven by target capital ratio	Optimising bank behaviour based on risk-adjusted return maximisation programme
Measurement of stress	Balance sheet liquidity (λ)	Liquidity generation capacity, net funding gap	Distribution of liquidity buffers across banks and across severity of shocks	Loss exceeding capital ratio threshold	Liquidity buffer (liquidity needs exceeding liquid assets), losses	Credit losses and output macro model	Capital shortfalls
Type of systemic stress	Contagious liquidity runs (rollover stops), network effects	Contagion through common exposures and interbank network	Second-round effects driven by bank responses	Contagion through network effects	Bank default, AFS and liquidity hoarding	Feedback effects on real economy via bank lending	AFS, interbank contagion
Network	Interbank spillover risks	Classic network model, contagion driven by default threshold	No interbank network	Classic network model, contagion driven by default threshold	Interbank contagion caused by liquidity withdrawals and bank failure	No interbank network	Both static and dynamic (agent-based) network models

4.2 Attribution analysis – how much can it matter?

The models that include both solvency and liquidity risk provide a quantitative indication about the attribution of liquidity risk to the overall stress test outcome. For this purpose, the simulation output of each model has been broken down into the main attributing factors, ie different channels of credit risk and liquidity risk. In most of the models, credit risk dominates the first-round effect. It is usually measured in terms of a decline in the solvency ratio. In many cases, the second-round – or systemic – effects are caused by the interaction between solvency and liquidity risk, which makes it hard to distinguish the attribution of liquidity or solvency risk in isolation. Still, for the purpose of the attribution analysis the output of the models was broken down along the main risk drivers, where possible.

The attribution analysis is also useful from another perspective, since it enables a comparison of the favourable effect of banks' mitigating actions in response to the scenario, with the adverse impact of second-round effects caused by collective responses. Such reactions might be rational from an individual bank's perspective; they are modelled by dynamic balance sheet assumptions and behavioural rules. However, collective responses by many banks at the same time can be detrimental to the stability of the system as a whole. Most models simulate the impact of each stage of the stress scenario and so provide insight into the effect of mitigation actions versus the systemic feedback effects.

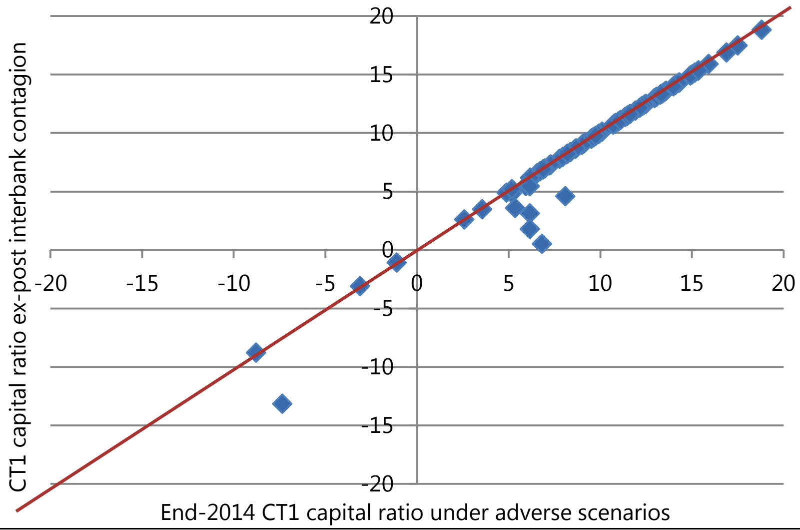
4.2.1 Model outcomes

Simulations with integrated stress testing models show that liquidity risk contributes substantially to the impact of a stress scenario. In most models, it amplifies the initial effect through various channels of contagion, in which behavioural responses by banks are a driving force. The contagion effects feed back into banks' balance sheets and P&L by raising default risk, reducing asset values and increasing funding costs. The additional adverse impact on banks' capital ratios may exceed the initial shock effect. The overall impact of a shock on banks is substantially underestimated if the solvency test is run in isolation from liquidity risk, and this underestimation tends to increase with longer stress scenario horizons.

While the ECB stress testing model focuses on the solvency impact of a stress scenario, it also includes bank reactions which trigger systemic contagion (Henry et al (2013)). Banks whose capital ratio falls below a certain threshold are assumed to default on their interbank liabilities. This amplifies the initial shock effect and has a substantial additional adverse impact on the capital ratio of banks (Graph 3). Another channel which amplifies the effect on banks' capital ratios works through banks' managerial defensive actions that feed back into the macroeconomy, thus raising the default risk of bank borrowers (Graph 4). The bank reactions are driven by a rule for optimising behaviour, based on risk/return portfolio management that may affect credit supply. Optimising the funding structure is part of this rule. In the model, the liquidity position is improved by investing in low risk/low return assets at the expense of loans.

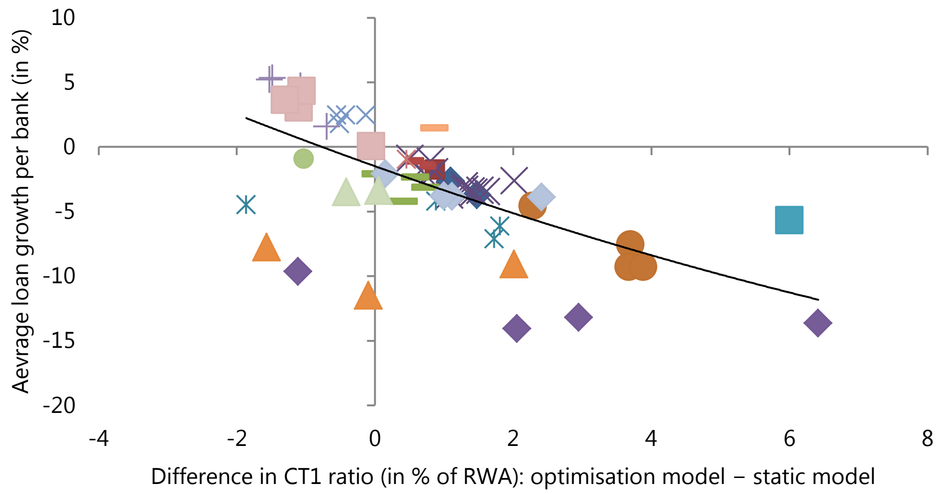
First-round losses under the adverse scenario vs second-round losses taking into account interbank contagion

Graph 3



Impact on CT1 ratio from allowing for (optimised) managerial actions

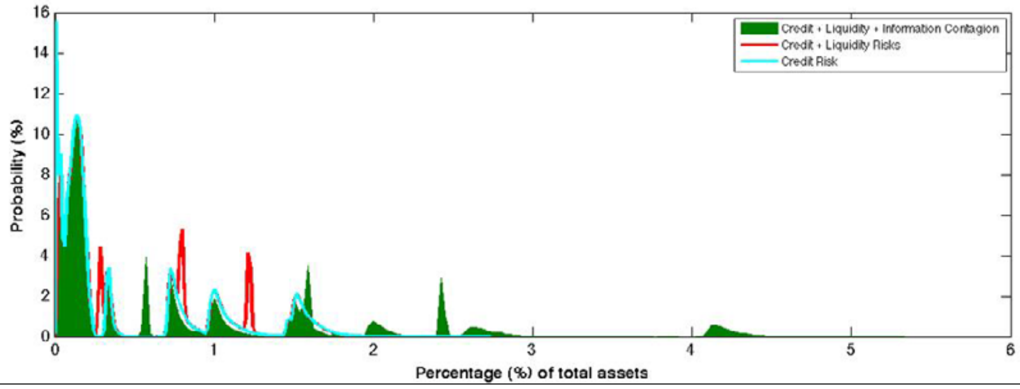
Graph 4



Liquidity risk plays a key role in the MFRAF model of the BoC (Gauthier et al (2010)). The risk stems from a potential liquidity run on the bank, which is endogenous (driven by the strategic uncertainty of bank creditors). The liquidity loss following a run is assumed to equal 2.25% of RWA, which is a somewhat arbitrary number but based on the BoC's limited experience of bank runs. Another determinant of the liquidity loss is the amount of short-term liabilities that is vulnerable to a run. The liquidity runs are also contagious in the sense that they can engender fire sales of assets. Graph 5 shows that liquidity risk and contagion effects have a substantial attribution to the total loss probability, which exceeds the initial credit risk effect.

The relative impact of different kinds of shocks

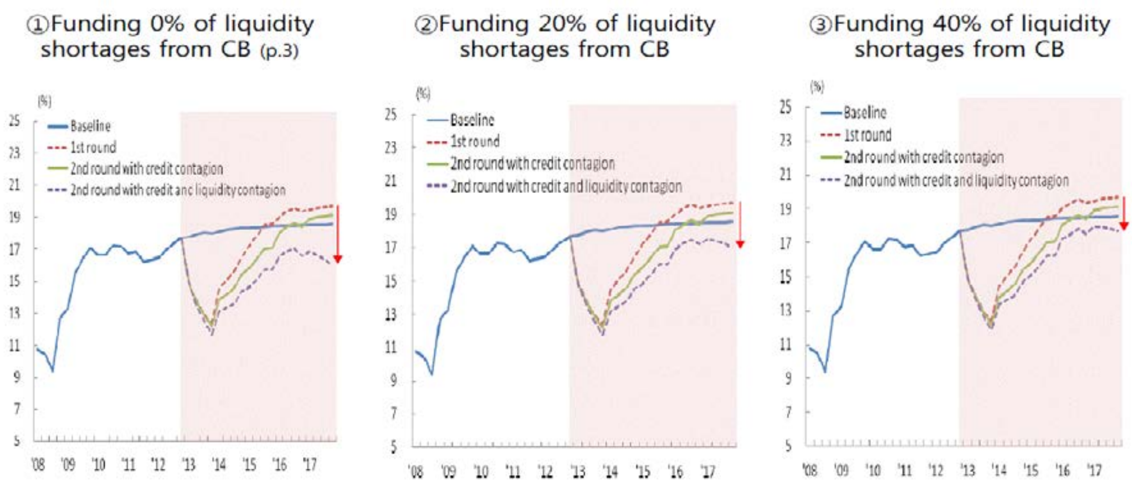
Graph 5



In the BoK's Systemic Risk Assessment Model for Macroprudential Policy (SAMP) model, liquidity risk plays an important role in the contagion of the initial shock effects (Bank of Korea (2012)). A fall in banks' capital ratios gives rise to liquidity run-offs, liquidity hoarding and asset fire sales by counterparties in the interbank market. These reactions, in turn, affect the solvency of banks and thereby manifest the interaction between solvency and liquidity risk. Besides the capital ratio, the liquidity ratio acts as a trigger for responses by banks as well, and this can have wider adverse effects. Graph 6 shows that contagion effects substantially contribute to the overall scenario outcome, particularly in the medium term. Liquidity contagion in particular prevents banks' capital ratios from returning to pre-stress levels. The SAMP model also allows for simulation of the effects of central bank measures, which can substantially mitigate the contagion effects on the banks (shown by the upward shift of the purple dotted line moving across the graphs from left to right).

Scenario analysis – contagion effects

Graph 6

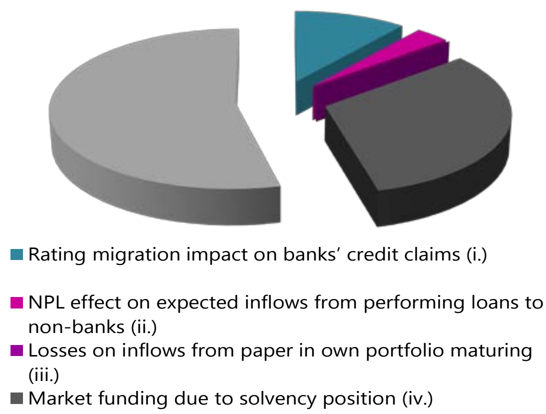


The OeNB model (Puhr and Schmitz (2014)) allows for a rather detailed breakdown of stress test outcomes into risk drivers (Graph 7). The interaction between liquidity and solvency risk factors runs through various channels. Solvency risks impact liquidity through reduced pledgeability of assets and reduced cash inflows. The liquidity to solvency link runs through both a cost of funding shock and asset fire sale losses. Simulations of an illustrative credit and financial market scenario show that the overall impact would have been underestimated by one third if the solvency test were run in isolation. Asset fire sales turn out be the main interaction channel from liquidity to solvency, contributing 25% to the total loss in the solvency stress test. However, parameter uncertainty is high with regard to asset fire sales. In the liquidity stress test, the isolated impact of liquidity shocks accounts for about 54% of the decline in banks' counterbalancing capacity. A loss of market access is the most important interaction channel from liquidity to solvency.

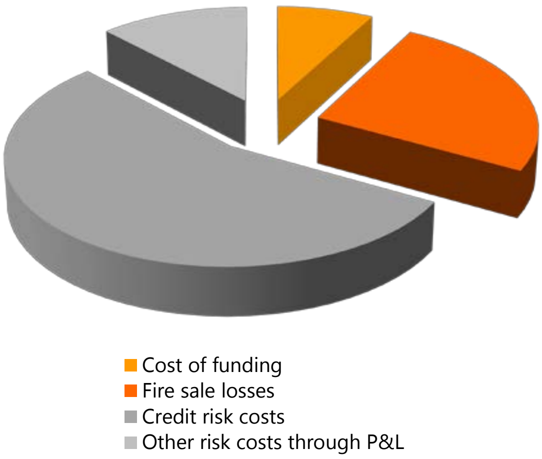
Attribution in different types of stress tests

Graph 7

Liquidity stress test (share of total impact on cumulated counterbalancing capacity)



Solvency stress test (share of total impact on P&L losses)



Source: OeNB

The CBoN model adds liquidity risk to the solvency stress test by assuming a shock to banks' cost of funding and rollover stops in banks' wholesale funding. Banks react to higher funding costs by raising the rates charged on loans, which feeds back to both loan growth and economic growth. The closure of wholesale funding markets forces banks to sell assets, which raises haircuts on asset values. The attribution of liquidity risk and higher haircuts reduces the capital ratio by approximately one additional bp in an average stress scenario. On the other hand, including the dynamic balance sheet assumption (ie banks increase loan margins and reduce corporate lending) will help boost the stressed capital ratio over the scenario period back to the initial level.

4.3 Balance sheet assumptions[38]

Balance sheet assumptions in supervisory stress tests are an area known to be in need of further refinement. Although banks' balance sheets change over time, many supervisory stress tests nevertheless assume a static balance sheet.[39] While such a simplifying assumption controls for behavioural effects and allows for greater comparability of results, it is unlikely to be realistic. Some supervisors also use banks' forecasts for the evolution of their balance sheet, but this introduces the potential for institutional gaming and results in a lack of comparability. This section discusses some pioneering work with regards to approaches to bank balance sheet optimisation in supervisory stress tests.

Balance sheet changes can be triggered by banks' strategic actions (due to risk management, profit maximisation or shareholder value maximisation objectives) or trends and risks in the macroeconomic environment (eg intensified competition, business cycle and crisis periods).

[38] Drafted by G Hałaj (European Central Bank)

[39] For example, the EU-wide stress test exercises coordinated by the European Banking Authority in recent years.

The challenges that arise when assuming dynamic balance sheets for the assessment of the resilience of a bank to future adverse conditions are not only related to changing volumes, but also to behavioural parameters. Consequently, allowing for the balance sheet to evolve in stress testing creates unnecessary methodological leeway in the bottom-up approaches that can also be difficult to explain and justify (or challenge) from the top-down perspective.

The length of the assumed stress test period is relevant as well. Solvency stress testing exercises consider a longer time period, and in this context it is more natural to assume that the balance sheet composition and size changes. Liquidity stress tests generally take a shorter-term perspective but may refer to a much more volatile chain of events that trigger more pronounced balance sheet responses from banks. For instance, a weekly outflow of retail deposits above an alerting threshold (eg 5%) can induce managers to sell liquid assets (or less liquid ones depending on market liquidity and the economic outlook) to improve cash flows, increase central bank eligible assets or quickly shorten the maturity profile of their assets to improve liquidity ratios.

Banks take deliberate actions to change the composition of their balance sheets to meet their economic goals. These goals may vary over time and are influenced by macroeconomic and financial conditions. The complexity of managing a bank's balance sheet is related to the fact that there are multiple objectives to be satisfied, and it is not obvious how shareholders, managers and other stakeholders weigh the importance of various criteria. The objective could be to maximise shareholder value, measured by the value of the call option on the assets with the debt volume as the strike price of the option, as in Merton's (1974) classic article. It could be to maximise income (in the short or longer run), as proposed by Thakor et al (2010) and Yilmaz (2009), or risk-adjusted profit (Stoughton and Zechner (2007)), or risk-constrained profit (Danielsson et al (2008)). The profit maximisation should also account for liquidity risk minimisation, whereby banks want to minimise the risk of a liquidity shortfall. Last but not least, the risk of bankruptcy should be factored in, also reflecting the resolution regime. In some models (eg in the seminal Leland and Toft (1996) contribution or in Yilmaz (2009)), bankruptcy occurs if the value of the assets falls below a given target level, but there are also examples of a different approach where the firm does not default but pays a penalty cost for being in a state of default, and in the optimal case these costs prevent it from entering bankruptcy (eg Browne (1995), Hałaj (2008)). Additionally, as discussed in the prior section, banks need to meet certain regulatory constraints.

The definition of banks' optimisation function is thus a complex problem. A rational formulation of the bank's optimisation problem may be complicated by behavioural aspects of the banking business (competition for market share, "following the crowd" in risk management or product choice).

Optimisation techniques can be used to model the rational choices of banks in structuring their balance sheets. The optimisation approach to the bank's asset and liability management dates back to Kusy and Ziemba (1986). The strand of research uses stochastic programming techniques from operations research (Consigli and Dempster (1998), Klaassen (1998), Ferstl and Weissensteiner (2011)), which in practice are well suited for risk management problems operating with granular portfolios and requiring many decision variables. Specifically, static one-period models are computationally tractable (ie easy to solve and to embed into larger stress testing frameworks).

Risk preferences are important drivers of decisions, also in the banking context. In the traditional banking literature (Baltensperger (1980), Boyd and De Nicolo (2005), Pelizzon and Schaefer (2005)), banks are assumed to take investment decisions assuming risk neutrality. In contrast, others assume that decisions are risk-sensitive (Howard and Matheson (1972), Danielsson et al (2002), Cuoco and Liu (2006)). Banks are assumed to be risk-averse in these setups, consistent with the capital management practice where Risk-adjusted Return on Capital (RAROC) and Risk-adjusted Return on Risk-adjusted Capital (RARORAC) support decisions about the optimal allocation of assets.

Dynamic balance sheets are embedded in the existing supervisory stress testing frameworks of some central banks. As Borio et al (2012) note, some stress test models allow for the possibility that banks adjust their balance sheets in response to shocks, although so far only through mechanical rules of thumb. For example, the Bank of England developed a stress testing model (RAMSI) that allows for changes in asset composition when banks make profits (or losses). The model contains a set of reinvestment rules assuming that banks target their capital ratio and try to maintain the product structure of their assets. On the funding side, a set of mechanical rules define the impact of an (exogenous) stress on the funding sources.

Similarly, the DNB model (van den End (2010)) implements second-round effect rules that model banks' reactions to liquidity shocks shifting the LCR below the regulatory 100%. The order in which banks substitute their assets to restore liquidity depends on their specialisation. The funding stress in the approach taken by the BoC uses cooperative game theory to calibrate the risk of a run on a bank and potential problems with the rollover of funding sources (see Anand et al (2014)). In the OeNB model (Puhr and Schmitz (2014)), a funding shock leads to a deleveraging of bank balance sheets; as a rule of thumb, banks sell all assets in their counterbalancing capacity (after having run down cash and central bank balances to zero) proportionally. See Appendix A for a detailed description of the models.

The ECB stress testing model uses an optimisation-based model whereby banks adjust their asset structure in response to shocks to parameters (eg expected loss) of their asset categories, also via changing solvency and liquidity constraints (see Appendix A, Hałaj (2013) and applications in the ECB Occasional Paper (2013)). The balance sheet is aggregated, reflecting data availability but also reflecting a compromise between the granularity corresponding to the real complexity of the balance sheet and the accuracy with which return, risk and correlation parameters can be measured. The optimisation process is modelled as a mean-variance portfolio choice with risky funding sources and risk limits that require a bank to keep the capital ratio above the regulatory minimum and to hold enough liquid assets to cover a potential outflow of funding sources. The capital ratio is defined as risk-weighted asset categories over CT1 capital. The setup is one period, so to run it over a 2-3 year horizon it is repeated sequentially; end-of-period structure in a period t is set as the initial structure in the period t+1. Although banks in the model are assumed to optimise the volumes of their asset categories with prices being given, the price adjustment effects can also be studied within the framework. For instance, the sensitivity of the pricing to the changing return and risk parameters was assessed by solving the model for the interest rate spreads on the loans that would maintain the structure of the balance sheet (and implicitly the market share) of the banks at the optimum.

An extension of the model to the multi-period optimisation brings intertemporal effects that smooth the adjustments of the asset structure. However, it is more complex to solve (dynamic programming techniques are required), and therefore requires use of a less granular balance sheet. Hałaj (2014) models a balance sheet composed of two asset classes and financed by homogenous deposits and capital. The two asset classes are loans (perfectly illiquid, ie only a maturing part can be reinvested) and securities (liquid but liquidation implying a cost captured by a haircut). The risk of the loans is a combination of credit risk and interest rate risk, whereas securities are subject to market risk impacting the valuation of the portfolio. The bank is assumed to optimise the future discounted flow of the risk-adjusted returns on capital with the returns reflecting the income from the loans and securities net the cost of funding. Investment strategies are constrained by the solvency and liquidity requirements. The solvency constraint has a regulatory form of the capital ratio (ie RWA divided by the capital) and the VaR-based constraint (requiring a bank to hold a capital buffer for 99% of scenarios of the net profit). The liquidity constraint is of a Liquidity-at-Risk type; banks are required to hold liquid assets (securities) to cover the 99% of scenarios with funding outflows. The framework is comprehensive enough to capture the main features of the banking business: risk/return trade-off and the risk-sensitive regulatory constraints that imply various non-linearities in banks' responses to the changing economic environment. At the same time, it is simple enough to be efficiently solved with the dynamic programming techniques, ie the standard optimisation tools.

The optimisation approaches to modelling dynamic balance sheets come with some caveats. First, mean variance-based techniques frequently produce corner solutions. This means that the theoretically optimal portfolios have a much less diversified composition in terms of different asset categories than those observed in reality. Second, optimisation on the funding side of the balance sheet does not have a well-established theoretical foundation. Third, it is costly to compute the multi-period models that stabilise the sensitivity of the optimal structures to changes in parameters. This limitation can be particularly problematic if many scenarios are considered. Fourth, it might be difficult to put holding strategies and the frequency of portfolio rebalancing into practice (depending on the bank's business model and transaction costs). Finally, some of the relationships assumed in the optimisation may break down once the size of the (stress testing) shock is large enough.

Finding a satisfying approach to modelling the dynamic aspect of banks' balance sheets is an active field of research that involves trying to capture the behavioural aspects of the banking system and banks' complex response functions to changing parameters of the market. Further work is necessary to advance supervisory stress testing toolkits to the next level of accuracy and sophistication.

5. Analysing systemic risk in supervisory stress tests

5.1 Crockett's macroprudential vision – how do we get there?[40]

In a 2000 speech that arguably first injected the topic of macroprudential goals into the supervision and regulation of banks, Andrew Crockett, then General Manager of the BIS, both highlighted the difference between the microprudential and macroprudential perspectives and underscored why the macroprudential perspective is important (Crockett (2000)). Crockett argued that the two distinguishing features of the macroprudential approach were (1) the focus on the financial system as a whole, with the objective of minimising the impact of distress on the economy; and (2) the recognition that aggregate risk is endogenous, ie dependent on the collective behaviour of institutions. Essentially, Crockett recognised the possibility that banks' actions could individually appear rational, but lead to undesirable systemic outcomes. Following this line of argument, Morris and Shin (2009) observed that the 2008–09 financial crisis illustrated the failure of risk-based capital requirements, the cornerstone of microprudential regulation, to capture important systemic risks, in part due to the failure to consider collective responses.

Over the last five years, solvency stress tests have developed into a tool that is sometimes described as macroprudential. However, the macroprudential aims of solvency stress tests are largely confined to developing stress scenarios that reflect potential cyclical threats (and often only those related to excess credit growth) to financial stability, and to ensuring that banks have sufficient capital to survive and continue credit intermediation if these risks are realised. Thus, solvency stress tests may act as a cyclical macroprudential tool, as they can incentivise banks to reduce risk-taking in areas deemed to pose systemic risk in stress tests. In parallel, liquidity shortages, broadly identified as the key factor exacerbating the global financial crisis, are starting to be captured in liquidity stress tests. The goal is to measure the resilience of individual banks to exogenously motivated funding run-off.

But such stress testing approaches fail to deliver the macroprudential perspective argued for by Crockett.[41] While it is uncontroversial that solvency and liquidity risks are interlinked in a crisis, and that recessions are more severe and long-lasting when the banking system is impaired, the implementation of an integrated solvency and liquidity stress testing framework with feedback to the real economy and

[40] Drafted by Cetina (Office of Financial Research).

[41] In practice, supervisory stress tests also face a number of other challenges, relating to data availability and endogenous feedback, among other things.

financial sector is generally still lacking. For supervisors to move towards adopting a Crockett-esque macroprudential view, alternative approaches are needed that consider the system more holistically by modelling interlinkages within the financial system, the potential impact of behavioural responses on the amplification of adverse shocks, and the macro-financial feedback mechanisms with negative consequences for the real economy.[42] As discussed in Section 4 – the overview of supervisory stress test models – some bank supervisors have already begun to incorporate macroprudential perspectives into their stress tests.

This section of the paper explores in greater depth two techniques which bank supervisors can bring to bear to enhance the consideration of systemic risk in stress testing, ie network analysis and agent-based models (ABM). Both techniques can help supervisors explore the potential systemic impacts on banks that are otherwise ignored in traditional solvency stress tests. These approaches, which are formulated at the level of individual institutions rather than in terms of aggregate quantities, are thus critical complements to more traditional econometric approaches to stress testing. Supervisors' development of these techniques can benefit not only their stress testing capabilities, but can also facilitate the development and evaluation of macroprudential tools and evaluation and analysis of microprudential policies and even the conduct of line supervision.

Network analysis allows supervisors to view exposures not on a counterparty by counterparty basis but to consider how credit and funding risk might propagate given the network of exposures. The failure of one or more banks in a stress test might have implications for other banks through credit or funding channels if they are exposed to banks that, in turn, are creditors of the failing institutions. Thus, network analysis moves supervisors towards a more systemic view – a deeper understanding of which institutions are central or peripheral in a crisis – and is a material improvement on bilateral exposure data in evaluating potential second-round effects on other institutions from credit or funding shocks (see forthcoming Cetina, Paddrik and Rajan). As will be discussed in more detail, when network data are complete, such analysis is largely assumption-free and merely a more holistic way of understanding risk propagation. When data on the network of exposures are partial, assumptions can be made to still use network methods to strengthen stress tests and supervisory analysis of risks. Work stream members evaluate various partial network models relative to data on full networks to provide perspective for supervisors on which models tend to generate outcomes most similar to the true network.

ABMs can make use of network data but take the analysis a step further towards realising Crockett's macroprudential perspective. Specifically, ABMs include behavioural assumptions that can illuminate how banks' actions might affect stress on other banks, credit intermediation and economic activity, and can thus guide the use of macroprudential policy to contain systemic risk.

The remainder of Section 5 will introduce each of these techniques, network analysis and ABMs. It will also provide an overview of implementation issues and discuss work stream members' applications of these tools in ways that can contribute to supervisory stress testing and/or policy analysis.

5.2 Network analysis[43]

Network analysis can help illuminate the transmission mechanisms through which solvency risk and liquidity risk interactions can spread across banks. The academic literature identifies two broad mechanisms for the interaction and spillover of risks. The first is precautionary liquidity hoarding, whereby banks that have suffered solvency shocks or deposit run-offs may decide to cut lending to their

[42] IMF (2014b).

[43] Drafted by K Anand (Bank of Canada) and I van Lelyveld (Netherlands Bank).

counterparties. These counterparties, in turn, anticipating the cut in funding, will also cut lending to their counterparties, and so on. Depending on the structure of the network and the distribution of initial shocks, such hoarding may ultimately lead to a freeze in aggregate interbank markets. This precautionary liquidity hoarding mechanism is, in fact, incorporated into the Bank of Korea's macro stress test model (Lee (2013), Gai et al (2011) and Arinaminpathy et al (2012)).

The second mechanism is that of Knightian, or strategic, uncertainty. It is typically costly for banks to monitor the activities of their counterparties in the wholesale funding market. An individual bank may be uncertain about whether other banks will roll over funding or carry out a run on a counterparty to which they all have exposures. However, in the event of a run, this will lead to a reorganisation of the interbank market, leading other banks to become exposed to strategic uncertainty and run risk. For large credit shocks and maturity mismatches on the balance sheets of banks, these dynamics can lead to a freeze in interbank markets (Anand et al (2012), Zawadowski (2011)).

Alternatively, due to balance sheet opacity, one bank may find it costly to value a counterparty's assets, which, in turn, depends on the ability to value the counterparty's counterparties' assets, and so on. As opacity increases, the cost of determining the value of a counterparty's assets, and those of the counterparty's counterparties, increases. As monitoring costs rise, banks optimally choose to cut lending, once again leading to a breakdown in wholesale funding markets (Caballero and Simsek (2013)).

While several promising network models have been identified, employing them in supervisory stress tests is a challenge, as measuring a network requires granular data on credit exposures and/or funding sources.[44] Even prior to the 2008–09 crisis, several countries had transaction level data available for important markets in their jurisdiction. The FSB Data Gaps Initiative has been instrumental in promoting more granular data collection in other countries as well. Nevertheless, data are generally not available beyond the existing regulatory perimeter. This means that domestic exposures to non-bank financial institutions are not tracked systematically[45] and that internationally data are only exchanged sporadically (eg Alves et al (2013)). Cerutti et al (2011) present an overview of the efforts in this respect. Thus, most empirical research focuses on the unsecured interbank funding market in a single country, ignoring international links or those to the non-bank financial sector.

The finding in the early literature that systemic risk is very low (eg Furfine (2003)) is driven partly by what is included as exposure and partly by abstracting from the dynamic nature of the network structure.[46] Here, we focus on the former. The credit risk type of contagion and the underestimation of systemic risk in this perspective might merely reflect data gaps: only the unsecured exposures have been used to assess the risk of contagion, but many other important exposures have been ignored, like the cross-holding of securities among banks and non-banks or exposures arising from derivatives, which proved problematic for AIG and its counterparties. Poledna et al (2014) show that contagion risk is heavily underestimated by only considering unsecured interbank exposures, which they estimate only represent 10% of total systemic risk. Moreover, for an accurate assessment, contingent cash flows that materialise in times of stress (eg margin calls in repos, re-margining payables in derivatives) need to be

[44] Especially on the liability side, this can be complicated, as banks, for instance, do not usually track their bonds in the secondary market. The BIS International Banking Statistics' Funding template, currently being rolled out, aims to fill this gap (Cerutti et al (2011)).

[45] With some exceptions, eg Solorzano-Margain et al (2013) and Miranda and Tabak (2013).

[46] See Upper (2011) for an overview of the earlier literature; and Degryse and Nguyen (2007); Elsinger, Lehar and Summer (2006); Van Lelyveld and Liedorp (2006); Upper and Worms (2004), for examples. Recently, for example, Glasserman and Young (2013) show that for a wide range of shock distribution and network structures, direct contagion will quickly peter out in the absence of an additional effect such as bankruptcy costs (Zawadowski (2011)), fire sales (Shleifer and Vishny (2011)), mark-to-market losses or subordination (Acemoglu, Ozdaglar and Tahbaz-Salehi (2015)).

included (see Cont et al (2013) for an application to the Brazilian financial network). These more complete exposure sets are relevant for both stress testing exercises and agent-based modelling.

Network models have been used to study liquidity contagion and for stress testing purposes (see Lee (2013) and Fourel et al (2013)). However, in order to perform proper liquidity contagion studies, it is necessary to study the multilayer structure of the financial system (Montagna and Kok (2013), Bargigli et al (2013) and Poledna et al (2014)). This approach is needed because banks may react differently in different markets. For example, in the event of a funding shock, a bank might reduce its unsecured lending. Of all the bank's unsecured lending, only the short-term bucket would be affected. This reduction, in turn, would affect other banks' funding, thereby transmitting stress to other banks in the system. As a consequence, it is necessary to have a comprehensive exposures network in order to adequately evaluate credit risk, but at the same time it is necessary to separate the short-term unsecured segment of the exposures network, in order to model funding risk contagion. However, data availability is a major hurdle.

As granular data on the full network might not always be readily available, several methods to approximate a network with the available data have been developed. Different methods exist to estimate networks from partial data by optimising over different subsets of network measures. For instance, a relatively simple concept is the degree of a node, which is the number of connections a bank has. The distribution of degrees of banks in the network is the degree distribution. The former is a local measure whereas the latter is global in the sense that it applies to the network as a whole. The aim is to discuss which partial network models best approximate as many measures of the underlying network as possible if only incomplete data are available.[47]

In what follows, the work stream has compared the performance of these algorithms in deriving the true network, in terms of topological measures and measures of risk. First, work stream members collected data for complete interbank networks from several countries. They then postulated that for each of these networks they only knew the total amounts lent and borrowed by each bank (ie they computed the marginal as though they had partial data). Using these marginals, work stream members estimated the true networks employing the different partial methods for deriving true networks. Finally, work stream members compared the estimated network matrices to the original complete network so as to evaluate the performance of the different partial network methods.

5.2.1 Analysing partial network models using complete network data

The work stream, in cooperation with researchers from other countries, collected 23 unique networks from 12 countries to consider which models of partial networks provide the strongest fit to data when the full network is, in fact, known.[48] This exercise is important because it can help guide supervisors in their choice of partial network model when complete information regarding bank exposures is lacking. (Appendix B gives more background information on the networks and lists the researchers involved.) As shown in Table 10, the models include networks of interbank exposures, payments systems, repo exposures and derivative exposures (CDS and otherwise). The work stream also included a forex swap

[47] See Newman (2003) for a description of the most commonly used measures.

[48] A number of researchers contributed to this network reconstruction exercise: Thiago Christiano Silva, Sergio Rubens Stancato de Souza (Central Bank of Brazil), Kartik Anand (Bank of Canada), Ib Hansen, Morten Haastrup (Danmarks Nationalbank), Dilyara Salakhova (Bank of France), Ben Craig, Soeren Friedrich (Deutsche Bundesbank), Ádám Banai, Bence Mérő (Magyar Nemzeti Bank), Cristina Conflitti, Stefano Nobili (Bank of Italy), Hwayun Lee (Bank of Korea), Serafín Martínez-Jaramillo, José Luis Molina-Borboa, Fabrizio López-Gallo (Bank of Mexico), Iman van Lelyveld (Netherlands Bank), Nick Vause, Laura Silvestri, Ujwal Shreyas (Bank of England), Rodney Garratt, Rosa Hayes (Federal Reserve Bank of New York), Sriram Rajan (Office of Financial Research).

market network and an equity cross-holdings network (in the other category). The table shows the minimum, median and maximum for the metrics included across the different network types.

Descriptive statistics for networks with full data used in analysis of partial network models

Table 10

	Types of Networks				
	Interbank	Payment	Repo	CDS	Other
Countries	CA BR BIS DK FR HU IT KR MX	BR MX US	DK MX	MX US UK	HU MX
Number of links	30 (587) 3084	149 (34335) 169027	18 (46) 74	70 (1317) 3267	99 (160) 221
Density (%)	1 (44) 100	1 (16) 43	4 (9) 14	1 (3) 4	2 (4) 5
Ave. Degree	4 (9) 26	3 (14) 29	2 (2) 2	2 (4) 5	2 (2) 2
Med. Degre	2 (8) 28	0 (7) 18	1 (1) 1	1 (1) 2	1 (1) 1
Assortativity	-.44 (-.31) -.12	-.52 (-.38) -.26	-.73 (-.44) -.16	-.79 (-.52) -.15	-.57 (-.44) -.31
Clustering	3 (26) 100	6 (12) 18	3 (3) 3	3 (11) 18	1 (4) 6
Core (%)	3 (43) 83	3 (24) 44	9 (13) 17	2 (8) 13	7 (9) 12
Error score (%)	0 (16) 47	3 (11) 27	22 (39) 55	2 (23) 61	33 (45) 57

BR = Brazil; BIS = BIS cross-border banking system exposure data; CA = Canada; DK = Denmark; FR = France; DE = Germany; HU = Hungary; IT = Italy; KR = Republic of Korea; MX = Mexico; NL = Netherlands; UK = United Kingdom; US = United States.

Although there is some heterogeneity within types of networks, the differences across types are larger (Graph 8). The density of interbank networks is generally higher although this is partly determined by the sample selection along national jurisdictions (eg the Canadian and French interbank networks). The density of payment and derivative networks is generally very low (especially for extremely large networks, such as the US Fedwire payments and the CDS networks). Correspondingly, the degree of interbank networks is larger, sometimes by a factor of five, than for all other networks.

As for local network structure, all networks display negative assortativity and positive clustering. Assortativity, which ranges from –1 to +1, measures how likely it is that nodes of a similar degree are associated with each other. A negative value means that smaller nodes tend to link up with larger nodes and vice versa. This is especially the case for CDS networks. In addition, clustering, which is defined as how often a bank's counterparties are counterparties in turn, is higher for the interbank networks compared to the other types.

Looking at the structure of these networks as a whole, both the interbank and the payments networks seem to be closer to the benchmark core periphery model, as these networks generally have lower error scores (with a rather large core).

5.2.2 Partial network methods applied

After considering the literature, the work stream was able to collectively implement the five methods listed in Table 11 on the network data summarised in Table 10. A more complete (and technical) description can be found in Appendix B. The work stream also considered several other methods but – for various reasons – decided against including them.[49] Another aspect to note is that some methods produce weighted (or "valued") networks, while others output adjacency matrices that only indicate the presence or absence of links. In addition, some partial network models produce a single matrix while others produce a series of matrices (also known as an ensemble). Finally, for comparative purposes we will present all the metrics for the original, observed matrix and for the maximum entropy solution.

49 The alternative methods considered, but for various reasons not implemented, were De Masi et al (2006), Hałaj and Kok (2014), Mastromatteo et al (2012), Moussa (2011) and Musmeci et al (2013).

Overview of the methods included

Table 11

Authors	Mnemonic	Short description
Anand et al (2014)	*Anan*	A "minimum density" method which minimises the number of links necessary for distributing a given volume of loans.
Baral and Fique (2012)	*Bara*	Uses a copula to allocate the marginals.
Battiston et al (2012)	*Batt*	A "fitness model" determines the likelihood of linkage, fitness being determined by capital.
Drehmann and Tarashev (2013)	*Dreh*	Perturbed maximum entropy matrices (with the RAS algorithm).
Hałaj and Kok (2013)	*Hala*	Assumes a probability map driving link probabilities. Set to be uniform for comparability.
Mastrandrea et al (2014)	*Mast*	Reconstructs the network with information on the degree distribution of the node.

Note: The mnemonic is simply the first four characters of the first author of the specific approach.

The *Anan* method is a heuristic that attempts to find the network with the fewest number of links, while preserving the interbank asset and liability constraints for all financial institutions. Additionally, the method attempts to shape the resulting output to display negative assortativity, ie institutions that have large interbank assets lend to other institutions with small interbank liabilities and vice versa.

The *Bara* method uses so-called copulas to estimate the structure of linkages between financial institutions. A copula in this case is a probability distribution that captures the dependencies between the lending and borrowing across different financial institutions. This information serves as a prior, which is fed into the maximum entropy routine, along with the interbank asset and liability constraints to produce an output network.

The third method – *Batt* – is based on a "fitness model". Each financial institution has a fitness score that determines the probabilities with which two financial institutions are linked. If both have a high fitness score, then the probability of a link is high. The fitness score of each institution is a function of its tier 1 capital: the more capital an institution possesses, the greater is its fitness. The *Batt* method produces an ensemble of adjacency matrices.

The fourth method – *Dreh* – is also based on the maximum entropy method where the prior for the arrangement of links is determined by simulating actual interbank networks. Insofar as those actual interbank networks fit a core periphery structure, the output from the *Dreh* method exhibits a dense core with large exposures and a sparse periphery with smaller exposures.

The *Hala* method is based on a so-called probability map, which specifies the probabilities with which any two financial institutions are linked. Since the construction of such a map crucially depends on jurisdictional features, we assume a uniform distribution for all pairs of links. The method proceeds as follows: first, a link is picked at random based on the probability map. Next, a number from the unit interval is drawn at random, which specifies the percentage of the borrower's liabilities that are satisfied by the lender. The procedure iterates until the lending and borrowing requirements for all financial institutions are satisfied. The output of the *Hala* method is an ensemble of weighted networks.

Finally, the *Mast* method is based on the fundamental principle of maximum entropy. The method generates a probability distribution that is free from biases – ie maximises the information entropy – and satisfies, on average, the interbank asset and liability constraints for all financial institutions. An ensemble of weighted interbank networks is then drawn from the estimated distribution. As a benchmark, we also include maximum entropy *(Maxe)*.

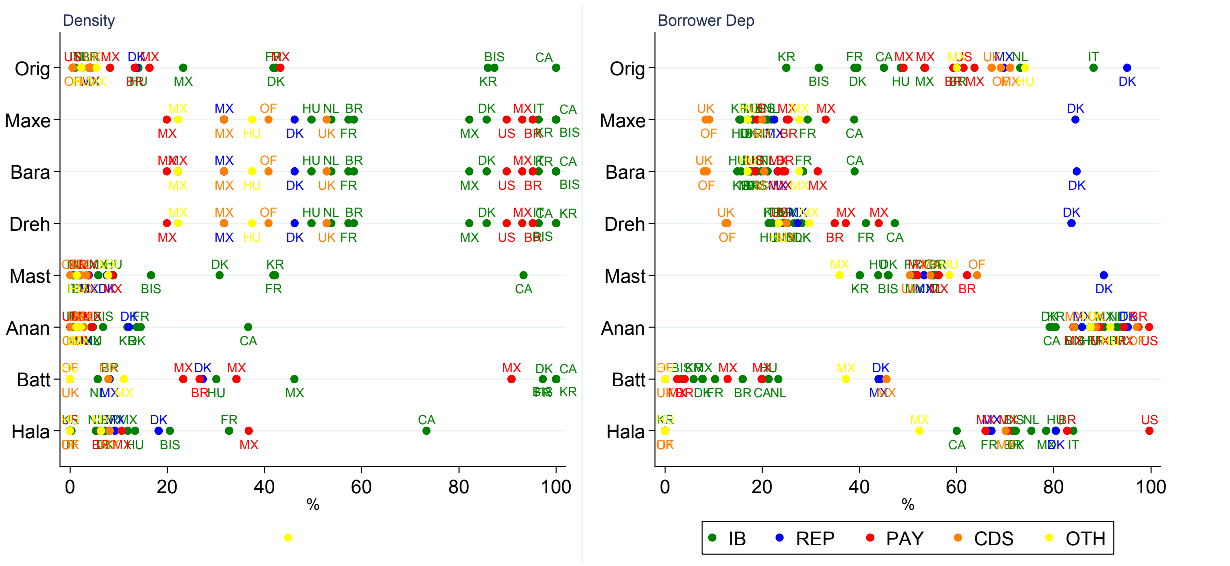
5.2.3 Results

Members evaluated the estimated matrices from each of the methods along several dimensions: (1) matrix metrics, (2) matrix similarity, (3) confusion matrices, and (4) counterfactuals: DebtRank and liquidity shortfall. Starting with the matrix metrics, the work stream computed a comprehensive set of statistics covering local and global network characteristics. For each network, the number of links, their density, the degrees, assortativity, clustering, the concentration of in- and outgoing links, the core size and core periphery fit (all defined in Appendix B) are computed. Second, work stream members computed how close the estimated networks were to their respective true networks by computing several similarity measures, namely the Hamming, Jaccard and Cosine distances and the Jensen-Shannon divergence measure. Again, definitions of all of these measures can be found in Appendix B, but essentially all these similarity measures are lower if the two matrices are more similar. To conserve space, we show only the Jensen-Shannon divergence in Table 12, since the other measures are broadly similar. Third, we have "confusion" matrices that measure the deviation – in terms of true/false positives/negatives of the estimated networks from the original. Finally, the work stream included the DebtRank and liquidity shortfall exercises to gauge the extent of contagion on both the asset and the liability side, respectively. Both exercises work through what the effects are of shocks passing through the network. For example, in the case of liquidity shortfall, the liquidity shock is assumed to be 10% of total assets. These exercises are not strictly related to the main purpose of this chapter, which is to compare the performance of different algorithms, but they are widely used in stress testing and thus are of interest. Although the DebtRank results are insightful, they are difficult to compare across networks and we will therefore not discuss them below.

Graph 8 (left panel) provides a scatter plot of the density of the original networks (top "row") and the density of the estimated matrices provided by the various methods. The sample includes a spread with some jurisdictions providing dense networks (CA, KR and BIS), while many others provide sparse networks. From the estimated matrices, we observe that Anan, *Hala* and *Mast* tend to estimate sparse networks for most jurisdictions, while *Bara*, *Dreh* and *Maxe* estimate denser networks – in many cases they estimate complete networks with a density of 100%. Depending on the network, this is thus an over- or underestimate.

Density and borrower dependence

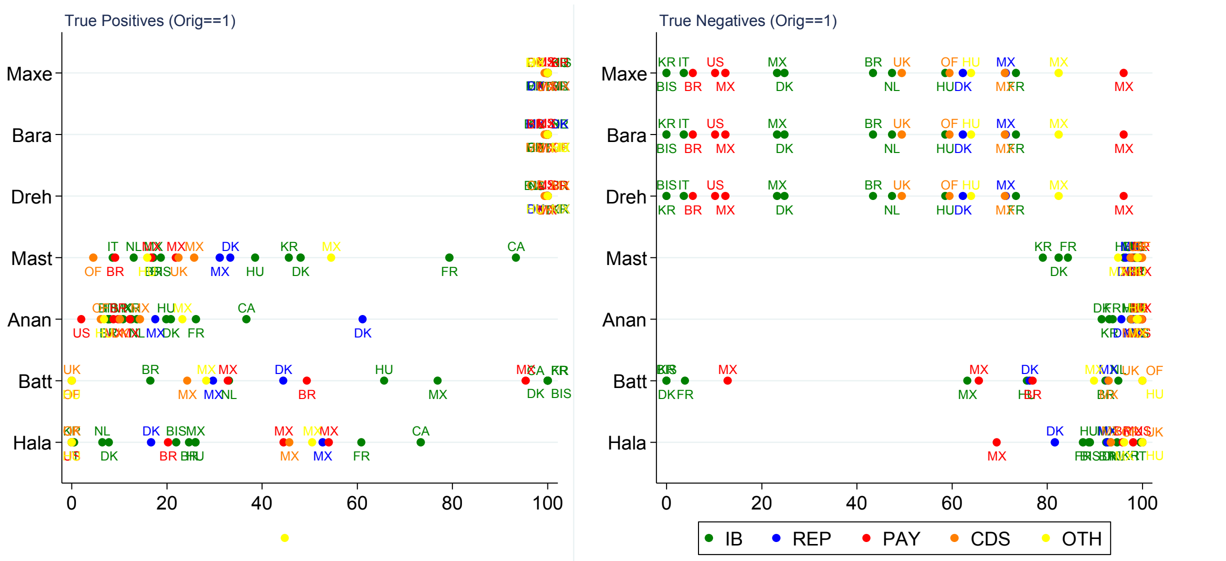
Graph 8



A similar broad classification of results is found in borrower dependency (Graph 8, right panel), which measures the reliance of individual banks on their largest creditor. The larger is the borrower dependency, the more concentrated are nodes' connections. Once again, the *Anan*, *Hala* and *Mast* methods produce more concentrated networks than the *Bara*, *Dreh* and *Maxe* methods. For the original networks, borrower dependencies ranged from 20–100%. The Hamming distance, which is supposed to be low if matrices are very similar, is lowest for maximum entropy (*Maxe*) and maximum entropy-based measures which are applied to relatively dense networks. The mean for *Maxe* Hamming values for interbank networks is 33,000, much lower than the corresponding values for payment and CDS networks. At the same time, the average density for interbank networks is 44%. The other distance measures, which focus on aspects of similarity, show a qualitatively similar picture.

The true-positives and true-negatives estimates from the confusion matrices shed further light on the structures of the estimated networks. As Graph 9 (left panel) demonstrates, the *Bara*, *Dreh* and *Maxe* methods are successful in identifying links among banks that are present in the original networks. This is a consequence of the maximal risk-sharing approach that underlies all three methods, resulting in these models estimating complete networks. On the other hand, the *Anan*, *Hala* and *Mast2* methods correctly identify which links are absent in the original networks (high values in Graph 9, right panel). This stems from the fact that these three methods tend to produce sparse networks. However, in sum, the accuracy of the various partial network methods is mixed, due to the identification of false positives and false negatives.

Correctly identified connections (true positives) and absence of connections (true negatives) Graph 9

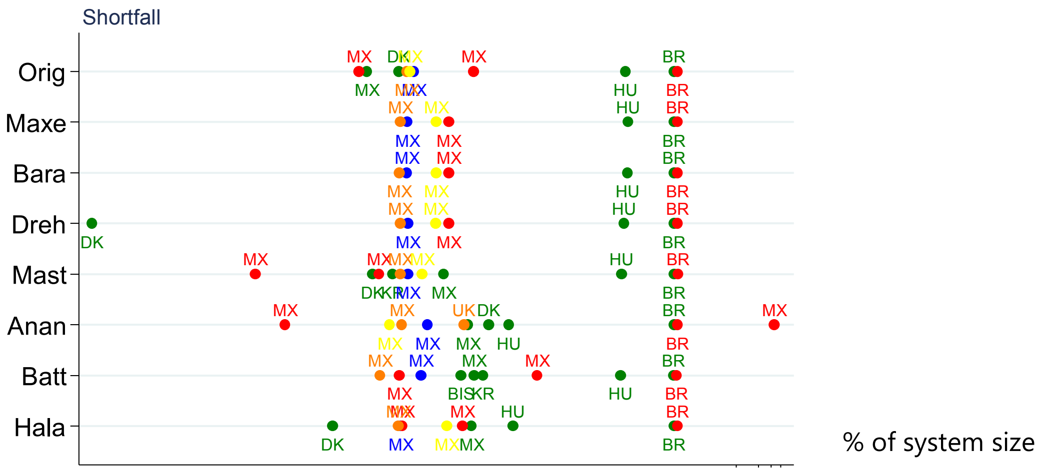


Finally, Graph 10 plots the aggregate liquidity shortfalls for the different networks and methods. We calculate the aggregate liquidity shortfall using the fixed-point argument of Lee (2013).[50] The results suggest that the *aggregate* shortfalls (summing across all banks) calculated for the original networks are

[50] Lee (2013) models the financial system as a set of banks connected through their interbank liabilities. Each bank liquidates assets and suffers a liquidity shock that will propagate to their counterparties in the interbank market proportionately to their liquid asset share of the banks' total liquid assets. Later, the additional shock suffered by these counterparties in turn propagates within the network in a similar way, iterated until an equilibrium is reached. For an individual bank, the liquidity shortfall is the equilibrium shock suffered by the bank in excess of its total liquid assets.

similar to the aggregate shortfalls from the estimated networks. However, individual banks' shortfalls – which are of interest for authorities wanting to intervene – may differ quite dramatically and have yet to be investigated.

Shortfall for different networks and methods — Graph 10



Goodness-of-fit measures for the various partial network models — Table 12

		Types of Networks				
Approaches		Interbank	Payment	Repo	CDS	Other
Maxe	Jensen	.04 (.42) 1.22	.13 (.42) .91	.11 (.3) .49	.54 (.64) .84	.44 (.61) .77
	Accuracy (%)	5 (63) 100	11 (44) 97	67 (70) 72	52 (61) 72	65 (74) 83
	Liq. Shortfall	0 (395) 2870	0 (810) 3239	0 (0) 1	0 (0) 1	0 (1) 2
Anan	Jensen	.31 (.74) 1.3	.44 (.87) 1.52	.03 (.11) .2	.71 (1.24) 1.87	.3 (.35) .4
	Accuracy (%)	19 (63) 99	59 (83) 99	91 (93) 95	94 (96) 99	95 (96) 97
	Liq. Shortfall	0 (323) 2877	0 (17193) 65535	0 (1) 1	0 (2) 4	0 (0) 0
Bara	Jensen	.04 (.42) 1.24	.14 (.42) .91	.11 (.3) .5	.55 (.65) .86	.44 (.61) .78
	Accuracy (%)	5 (63) 100	11 (44) 97	67 (70) 72	52 (61) 72	65 (74) 83
	Liq. Shortfall	0 (393) 2870	0 (810) 3239	0 (0) 1	0 (0) 1	0 (1) 2
Batt	Jensen	.27 (.84) 1.78	1.3 (1.92) 2.48	.49 (.49) .49	.42 (.42) .42	.39 (.39) .39
	Accuracy (%)	42 (74) 100	49 (61) 73	72 (81) 90	90 (95) 99	86 (92) 98
	Liq. Shortfall	0 (426) 2851	1 (1052) 3114	0 (1) 1	0 (0) 0	0 (0) 0
Dreh	Jensen	.19 (.6) 1.39	.29 (.59) 1.09	.17 (.4) .63	.72 (.83) 1.04	.6 (.76) .92
	Accuracy (%)	5 (63) 100	11 (44) 97	67 (70) 72	52 (61) 72	65 (74) 83
	Liq. Shortfall	0 (386) 2870	0 (810) 3239	0 (0) 1	0 (0) 1	0 (1) 2
Hala	Jensen	.06 (.64) 1.13	0 (.65) .91	.08 (.28) .47	.54 (.54) .54	.45 (.45) .45
	Accuracy (%)	14 (66) 99	58 (84) 99	73 (82) 91	92 (95) 99	94 (96) 98
	Liq. Shortfall	0 (322) 2874	0 (809) 3231	0 (0) 1	0 (0) 1	0 (1) 2
Mast	Jensen	.32 (.54) .86	.55 (.67) .73	.25 (.26) .28	.24 (.39) .51	.25 (.37) .5
	Accuracy (%)	29 (76) 99	62 (79) 88	88 (91) 95	95 (97) 99	93 (95) 97
	Liq. Shortfall	0 (382) 2877	0 (1087) 3262	0 (0) 1	0 (0) 1	0 (1) 1

The values provided in each cell are the minimum (mean) and maximum for the particular metric and network type.

5.2.4 Implications for supervisors' use of partial network models

The networks considered in this project vary greatly, both in size and composition. This heterogeneity is reflected in the quality of the different estimates obtained. As a general rule of thumb, dense networks are well estimated by algorithms in the maximum entropy group. However, significant differences may arise in estimates of the lending / borrowing dependencies and the Herfindahl indices (defined as sum of the squared "market" shares).

The maximum entropy method has, at its root, a simple risk-sharing mechanism, which implicitly assumes perfect competition, ie all banks are equally willing to accept an equal share of risk. Consequently, the Herfindahl indices and dependency measures are all typically small. However, for those networks where these statistics were reported, we find that the *Dreh* and *Bara* estimates perform better than *Mast* and *Maxe*.[51] The reason for the *Bara* estimate's superior performance is that it attempts to fit a core periphery structure into the estimate, which forces some banks to have a larger market share. However, the *Bara* method is based on fitting a copula to the aggregate interbank assets of banks using maximum likelihood estimation. For small networks, there may be too few data points for this estimate to be reliable. In terms of the DebtRank results, all three methods perform equally well in ranking the bank that has the highest DebtRank score in the original network.

In sum, this suggests that the *Bara* method is best suited for interbank markets that are expected to be dense and have a distinct core periphery structure.

For sparse networks, such as CDS networks, the *Anan*, *Hala* and *Mast* estimates are better fits. The *Anan* code, in particular, is designed to produce minimally dense networks. Both *Anan* and *Hala* rely on a "probability map": in *Anan*, the probability that one bank is linked to another depends on the relative sizes of the two banks, while in *Hala* a uniform probability was selected. However, as both sets of authors point out, alternative specifications incorporating institution-specific details may be used. The *Mast* method does not require any such additional information, but instead derives a maximum entropy (information theoretic) probability distribution for the interbank network, where constraints for the aggregate interbank positions of individual banks bind, on average.

Thus, between the three methods, the *Anan* estimate is always the least dense and most concentrated. The *Hala* and *Mast* estimates are denser and less concentrated. In particular, the *Mast* estimate for the average borrower/lender dependency and the Herfindahl indices are closer to those of the original matrix. A similar picture emerges for the core size and error score. Thus, while the *Mast* estimates only satisfy the interbank asset and liability constraints, on average, the ensemble average matches the true statistics best for sparse networks.

Comparing the three methods in terms of DebtRank outputs, the *Anan* estimate outperforms the *Hala* and *Mast* estimates in terms of correctly ranking the bank with the highest DebtRank score, for both sparse and dense interbank networks. This, potentially, suggests that DebtRank is linked to disassortativity, as this is one of the key features of the *Anan* algorithm. The *Hala* estimate is the weakest at matching the ranking of banks, according to their DebtRank scores. This suggests that where supervisors are most concerned with identifying the bank with the largest systemic footprint, the application of *Anan* to partial data sets might contribute something to the assessment.

In sum, both the *Anan* and *Hala* estimates serve as useful benchmarks. As an extreme, the *Anan* estimate provides useful information for how sparse a network can be made, while still ensuring a certain volume of interbank activity. Such information is useful when thinking about the ramifications of a liquidity crisis and the worst-case scenarios.

5.2.5 Issues for further work

This exercise has provided many useful insights, but several issues merit further work. For most networks, the algorithms ran with sufficient speed. For larger networks, however, the run time was becoming

[51] The *Dreh* approach is based on the maximum entropy method. However, as the authors note, "[a]n ME matrix satisfies simultaneously two conditions. First, the sum of the entries in each row / column corresponding to a particular bank equals the aggregate level of this bank's liabilities / assets vis-à-vis the other banks in the system. Second, the interbank assets and liabilities of each bank are distributed as uniformly as possible across the other banks in the system. Since the latter assumption is clearly ad hoc, we randomly simulate other interbank matrices that are consistent with the observed data."

significant (ie several days). Moreover, for the US Fedwire, the *Mast* method turned out to be infeasible. For both the Fedwire and the CDS networks, the *Batt* method was problematic. Since ever larger sets are becoming available, this scalability issue merits further thought.

Furthermore, to keep the project manageable, researchers have judiciously chosen either representative or especially interesting periods, and so it is not clear whether the results hold universally and how robust they are to various assumptions. Some jurisdictions have partially tackled this issue by examining several time slices, but on the whole this has not been done systematically. In further work, such sensitivity analyses could help establish whether these results are stable over time.

5.3 Agent-based modelling (ABM)[52]

In general, the ability to directly correlate macro-level outcomes with changes in the underlying micro-level behaviour and parameters diminishes as the complexity of the studied system increases. One way to analyse how the complex interactions of many micro-level components impact the financial system is to model the micro components as "agents" using an agent-based model, or ABM.

Agent-based modelling enables the organisational intricacies of financial sectors to be captured through the design of different types of agents, each with their own heterogeneity, and is, thus, a method for analysing the financial sector (Bookstaber (2012)). ABMs can simplify the modelling of complex systems by including a set of individual agents, a topology and an environment (Farmer (2009)). In a typical ABM representation of a financial market, the market participants are agents, the network is the topology and the exogenous shocks that can affect agents or the topology are the environment.

Modellers using ABMs face a trade-off between complexity and explanatory power. To create an ABM, it is important to determine what features are salient in representing the system being modelled so as not to overly complicate the framework. For example, in designing a model of a single security market, you would want to focus on the participants and the rules governing their interaction (trade and price), and then focus on a set of specific environmental shocks. In reality, however, the rules governing agents' interactions may be far more complex and the shocks may be an indefinite set.

As an ABM is a simulation comprised of many agents and a set of rules or heuristics, it can be a challenge to build. There are many parameters to fit and many dimensions of output to monitor and evaluate. Thus, the next subsection seeks to offer a high-level perspective of the key considerations in the construction of ABMs.

5.3.1 How to build an ABM

Agents

An ABM can contain thousands of agents with various degrees of heterogeneity in their beliefs and capabilities. Identifying the right set of agents for the model requires forethought with regard to what specific relationships one wishes to explore. In this process, consideration needs to be given to what features or elements of each agent need to be captured so that they can mimic the behaviour of real institutions.

Traditional economic approaches to agent design usually focus on the role of intelligent (ie rational) agents that seek to maximise a utility function (eg profit). However, this approach relies heavily

[52] Drafted by K Anand (Bank of Canada), M Paddrick (Office of Financial Research) and L Valderrama (International Monetary Fund).

on agents having perfect information and proper knowledge of the long- and short-term implications of their decisions. In the real world, agents are often less than rational – an area of some interest for behavioural economics. In reality, agents can only optimise over a subset of the information available to them or rely on a selection of heuristics that have worked for them in the past.

The topology

The topology of an ABM is the mechanism through which agents can interact with one another in the model. It can be viewed as having two aspects: the rules and the link structure. The topology rules determine the communication forms that the agents can have with one another (ie the types of information and when and how they can be shared). The topology structure reflects the links that connect agents together to form a network.

The environment

The environmental factors generally can be thought of as exogenous shocks that occur to the model. These shocks can come in various forms: changes in agent behaviour, changes in topology rules, etc. Though the set of possible environmental factors can be infinitely large in variety, the number to be tested is normally finite and often predefined by the set of objectives used in the model's initial construction, such as stress tests or policies being evaluated by regulators.

Implementation

Due to the computational complexity of ABMs as a result of the large number of agents and parameters, modelling needs to be implemented using software. To some extent, this is inevitable for a complex model that seeks to describe the behaviour of many interacting, heterogeneous agents. Developing the code can be made more manageable by adhering to standard object-oriented design, which lays out the interactions and parameters in a more understandable way and makes the models easier to follow. This also allows other researchers to apply portions of the model in their own work and to enhance components of the model in the process.

The first software specifically designed for ABM development was called "Swarm" and was written by the Santa Fe Institute in the mid-1990s. Today, there are numerous software packages and libraries that have been developed to facilitate ABM creation, ranging from simple prototyping to scalable system tools (Nikolai (2009)).

Execution

While implementation is focused on the application of software code, the execution of how the model is then exercised can be varied based on the objectives of the users. The most traditional of these is the model's use for Monte Carlo simulations, where the significance of parameters can be evaluated and stochastic variables can be fully tested. This execution method allows for significance testing to be applied to the model, and the discovery of emergent outcomes of the model that result from the collective behaviour of all or some agents in the model.

Model calibration and validation

Methods for conducting empirical calibration and validation of ABMs have often been regarded as the Achilles' heel of the agent-based approach in economic modelling because of concern over the perceived lack of robustness tests. The concern comes as a result of the difficulty of doing significance testing over a set of non-linearities, stochastic dynamics, non-trivial interaction structures among economic agents and micro-macro feedback (Fagiolo (2006)).

Numerous strategies exist that are based on the type and quantity of data, which allow for direct and indirect calibration methods (Fagiolo et al (2006), Axtell (2005), Sallans et al (2003)). The most significant of these is where calibration can be done on both the micro and macro level. The micro approach works to individually calibrate agents to their specific behaviour rules, such that they reflect the heterogeneity of their parameters. The macro approach parameterises the global variables shared by agents to fit the macro variable outcomes of all the agents' behaviours.

When validating the model, it is common to use some variant of a generalised method of moments. For ABMs of financial markets, comparisons can be made between the kurtosis, autocorrelation and volatility of the model and that of actual data (LeBaron (2006), Paddrik (2012)). Similarly, Thurner et al (2012) look at the macro results that their ABM of banks and hedge funds generates for return distributions. The housing model of Geanakoplos et al (2012) compares the output to actual housing foreclosures and other housing metrics.

5.3.2 ABM application – an integrated stress testing model with feedback effects[53]

The ABM application described below is an attempt to provide a stylised stress testing model based on simplified balance sheets, taking the solvency-liquidity nexus and the macro feedback effects into account. This framework allows policymakers to examine the capacity and willingness of the banking sector to support the economy under stressful conditions.

The agents

The financial sector is a complex system made up of a large number of interacting agents which act according to behavioural rules that are state-dependent. The system is populated with three types of agents: N banks, a continuum of noise traders and equity investors. Banks manage their balance sheets actively through two decentralised credit and securities divisions. Each division chooses an optimal asset allocation to maximise profits net of directly attributable funding costs once the capital structure is endogenised as a function of risk. Asset allocation is subject to regulatory and funding constraints. Noise traders are passive investors with well-behaved demand functions subject to random liquidity shocks that generate a stochastic process in the value of their holdings. Equity investors are passive agents that follow simple heuristics: they inject or withdraw capital as a function of banks' excess returns relative to a benchmark. All agents are risk-neutral. The framework is a multi-period model. Agents' decision problems at each time step are summarised in Graph 11.

[53] Contribution from L Valderrama (forthcoming IMF working paper, 2015).

The agents’ decision problems at each time step

Graph 11

	Balance sheet composition	Balance sheet capacity
Banks	Manage actively their balance sheet optimize credit allocation rebalance securities' portfolio subject to regulatory/market constraints regulatory constraints for credit risk for market risk market constraint maximum leverage	Profits and losses receive revenue from interest income incur expenses from interest payments where capital structure is pinned down by regulation hit by loan impairment charges on new loans revise loan impairment charges on stock of loans incur net gains/losses on securities at fair value pay out dividends to shareholders Receive injection/withdrawal of capital by equity investors Need for recapitalization when regulatory capital falls below regulatory threshold Maximum leverage unsecured funding - excess equity returns secured funding - asset price volatility
Noise traders	Follow a random strategy with a bias towards mean-reversion Hit by liquidity shocks which affect their willingness to invest	Price shocks feed into (i) marked-to-market gains/losses; (ii) asset volatility which informs regulatory capital; and, (iii) maximum allowable leverage
Equity investors	Inject/withdraw capital in the banking sector as a function of banks' excess return over benchmark	Equity flows feed into banks' capital position
Environment	Credit risk (PD), market risk (securities' volatility) Liquidity risk (shocks to funding)	Credit growth, GDP growth, securities' returns

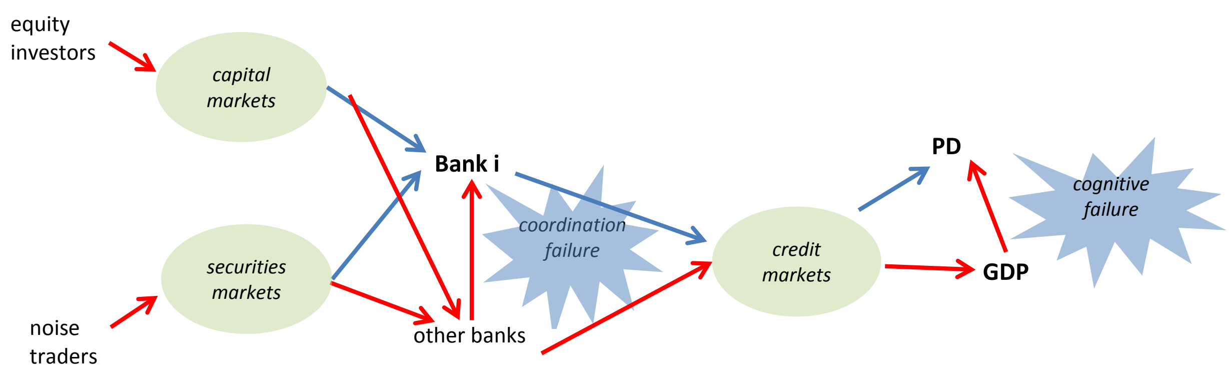
The topology

The mechanism through which agents interact with one another is threefold. First, banks and noise traders interact in the securities market through the market clearing condition. Second, banks interact with each other in credit markets. Their aggregate credit supply determines the macro path and triggers shifts in credit risk factors. Third, banks interact with investors in equity markets through the latter’s capital injections or withdrawals.

Banks are prone to coordination failure and are bounded rational agents.[54] In their credit allocation, banks take other banks’ credit behaviour as exogenous, even though, at equilibrium, they all act as clones. This lack of coordination creates a bias towards excessive credit growth. Also, they optimise over a subset of available information. They endogenise the direct effect of their actions on state variables (ie the effect of credit growth on risk factors) but take the path of state variables to which they contribute only indirectly as exogenous (eg the effect of credit growth on GDP). This cognitive failure yields lower credit growth than is socially optimal (Graph 12).

[54] This assumption is consistent with observed credit cycles. There is a growing literature on credit booms and busts featuring bounded rational agents and coordination failure. For a recent survey, see Burakov (2014).

Bank i's credit allocation problem Graph 12



This is a schematic diagram showing the information flows from other agents' behaviour which feed into bank *i*'s credit allocation problem. The blue lines represent the variables that are taken as endogenous and the red lines the variables that are taken as exogenous in the optimisation process.

The environment

The environment is defined by the set of economic and financial conditions that characterise the system. Given the purpose of the stress testing exercise, the model is run under a baseline scenario and a range of highly stressful operating environments under which banks' capital adequacy is assessed. The initial conditions are the following: (i) securities are undervalued; and (ii) credit growth is subdued. Graph 13 (left panel) shows the system dynamics for a baseline scenario over 60 time steps.[55] Low credit growth depresses real GDP, increases credit risk, pushes up RWA, lowers maximum available leverage and erodes banks' capital adequacy ratios. As banks optimise over credit supply, GDP growth recovers, asset prices trend up towards fundamentals, banks' capital adequacy ratios increase and the economy transitions towards steady state.

A feature of the model is the endogenous dynamics of shock propagation. That is, the realisation of an exogenous shock can trigger a cascade of endogenous shocks. An illustration is provided in Graph 13 (right panel), which shows a liquidity shock scenario. Here, a liquidity shock spread over t□[12,20] hits noise traders' holdings of securities. This shock generates a market shock – a drop in asset prices and a spike in asset price volatility – which triggers a bank funding shock – maximum available leverage declines – and morphs into a macro shock – GDP growth softens through a credit growth contraction, eroding banks' capital adequacy ratios.

Other adverse scenarios are generated including an adverse macroeconomic scenario, a funding shock scenario and a market shock scenario. These scenarios are endogenous to the economic and financial environment specified in the stress scenario, and, as a result, losses are automatically aggregated in the model and reflected in banks' capital adequacy ratios at the end of the period.

55 Each time step can be interpreted as a monthly period with the stress testing exercise spanning a five-year horizon.

Calibration

General parameters in the model are calibrated drawing on the literature on ABMs (eg noise traders' stochastic process, investors' behavioural rules).[56] Some model-specific parameters are calibrated to fit the value of key variables characterising the Austrian banking sector (eg rates, spreads, returns). The cost of economic capital draws on Basel II/III IRB risk weight functions for credit risk and market risk. Finally, a reduced-form macro model is estimated using data for key Austrian macro-financial variables.

The results and policy implications

The simulations show two key results. First, the bias in credit growth generated by bounded rational agents depends crucially on the phase of the economic cycle. Whereas in good times, banks generate excessive credit growth, in bad times they grant too little credit, which magnifies the length and severity of recessions. Second, for the same set of calibrated relationships, banks may act as stabilising/destabilising agents that mitigate/amplify the interplay between macro shocks and financial shocks depending on the environment underpinning their asset allocation. Two examples related to the securities markets and credit intermediation are provided below.

Banks' decision to unwind their securities portfolio is based on any of the following grounds: (i) banks are hit by a leverage constraint forcing them to cap their position; (ii) elevated market risk makes it too expensive to fund banks' asset position with economic capital; (iii) banks find it optimal to unwind their portfolio to free up resources for their credit operations; (iv) assets become overvalued. Whereas the first channel is related to banks' balance sheet capacity, the last three channels are associated with balance sheet composition. When any of the first three channels is activated in a downward market initiated by noise traders' liquidity shocks, banks' deleveraging contributes to a downward spiral in asset prices, triggering a fire sale mechanism, which further erodes banks' balance sheet capacity, thus weakening their capacity to provide credit and depressing GDP growth. By contrast, the last channel contributes to stabilising financial markets, as banks act as value investors that make investments based on fundamentals. Likewise, banks may decide to cut credit to the broader economy for three reasons: (i) credit allocation is constrained by thin capital buffers, which may lead to a sudden decline in available funding; (ii) credit risk is heightened, which increases expected loan loss provisions and the cost of economic capital; or (iii) banks find it optimal to reallocate available funding to the asset portfolio to exploit mispricing. If a credit crunch occurs in an economic downturn, aggregate credit behaviour will amplify the severity and length of the recession.[57]

Overall, the model shows key non-linearities due to: (i) the interplay between different bounded rational agents; (ii) the transition between states with binding and non-binding constraints; and (iii) the endogenous dynamics triggered by shocks transmitted through banks' balance sheet capacity and their optimisation process.

[56] The main reference is Thurner et al (2012).

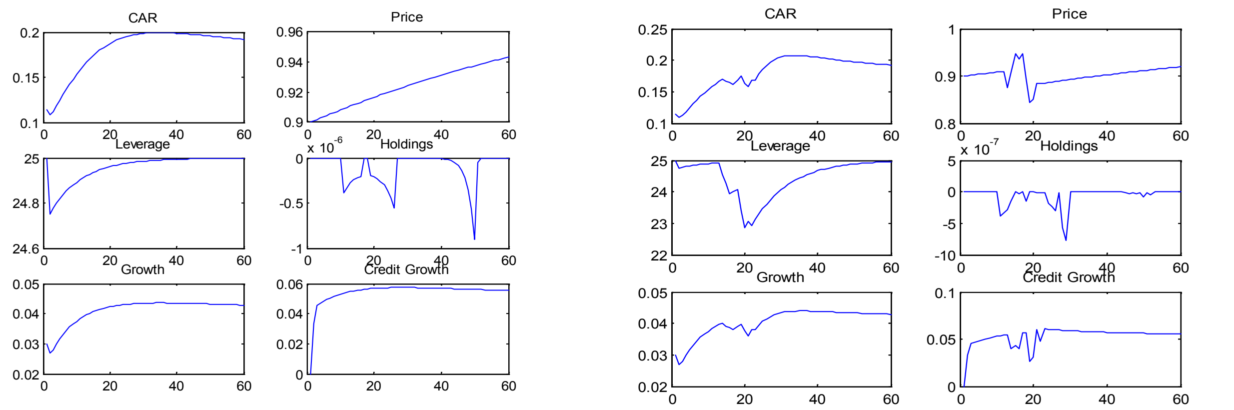
[57] This is due to the reduced-form econometric specification of the macro feedback channel. In a general structural model, the effect of credit bank behaviour on the business cycle is likely to depend on the source of the shock.

Evolution of the state of the banking sector, the securities market and the real economy

Graph 13

Baseline scenario

Liquidity shock



Graph 13 (left panel) shows the evolution of the state of the banking sector, the securities market and the real economy under the baseline scenario. CAR depicts the capital adequacy ratio of the banking system subject to a regulatory capital framework. Price reflects the market price of securities with a fundamental value of 1. Leverage denotes the equilibrium leverage of the banking system under a time-varying funding constraint. Holdings reflect the amount of securities held by the banking system. Growth refers to GDP growth. Credit growth represents aggregate credit growth. The dynamics are driven by subdued credit growth and the asset price shock at t=0. Low initial credit growth depresses real GDP, increases credit risk, pushes up RWA, lowers maximum available leverage and erodes banks' capital adequacy ratios. As banks optimise over credit supply, GDP growth recovers, asset prices trend up towards fundamentals, banks' CAR increases and the economy transitions towards steady state.

Graph 13 (right panel) shows the dynamics of the banking sector, the securities market and the real economy under an adverse scenario generated by a noise trader liquidity shock spread over $t \in [12,20]$. Two aspects are noteworthy. First, the initial shock triggers an endogenous wave of additional shocks. Noise traders' impaired liquidity leads to higher asset price volatility (market shock), decreases banks' maximum leverage (funding shock) and depresses GDP growth (macro shock). Thus, the model illustrates the potential for shocks to the non-bank financial sector to impact banks and the real economy which is relevant to supervisors' approach to scenario design. Second, banks' solvency position, credit growth and GDP growth remain subdued beyond the period of market stress due to feedback effects between the banking sector and the real economy.[58]

5.3.3 Assessing the dynamics of fire sales with ABMs[59]

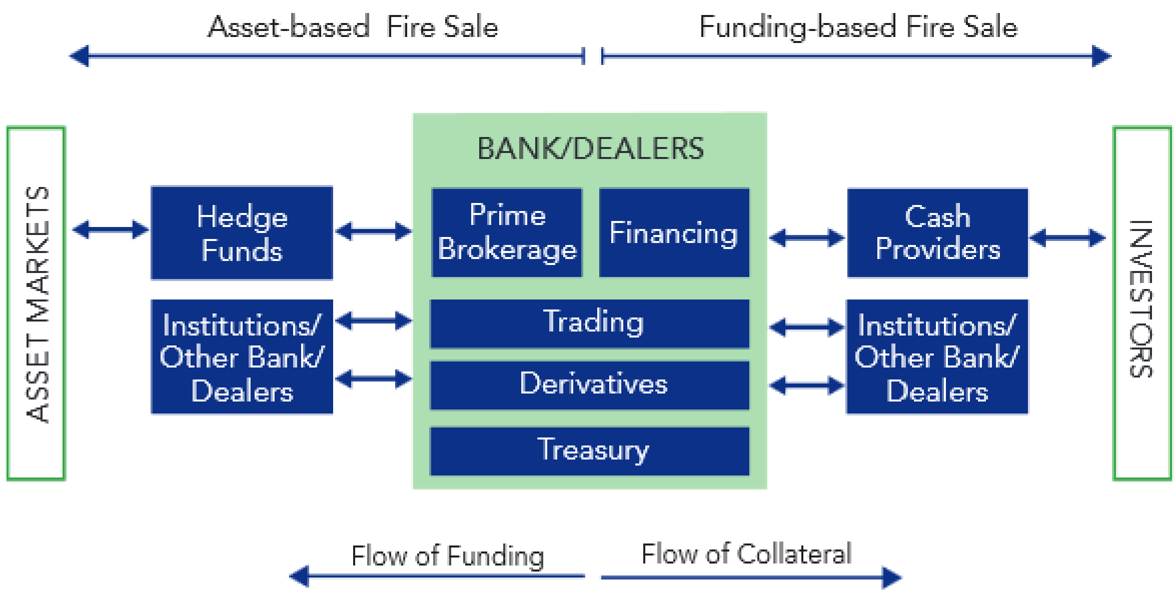
In order to depict fire sales, Bookstaber et al (2014) use an ABM to provide a system-wide view of the possible transformations and dynamic interactions of agents within the financial system. The model encompasses the suppliers of funding such as money market funds through the channels of the bank/dealer to the financial institutions that use the funds, as well as the collateral that passes in the opposite direction. This will enable a more dynamic approach to stress testing.

58 In the absence of second-round effects on the real economy, the stress test would be unable to reflect the compound effect from credit growth dynamics on risk factors through the GDP channel, dampening the effect of a liquidity shock on the soundness of the banking system.

59 Contribution from R Bookstaber and M Paddrik (OFR).

Financial system funding flows

Graph 14



This model focuses on the intermediation function of banks/dealers, such as their role in maturity, liquidity, credit and collateral transformation. Graph 14 shows the components of the banks/dealers and links to borrowers and lenders, following the funding map developed by Aguiar et al (2014). Graph 14 depicts the connections among three agents within the model: banks/dealers, hedge funds and cash providers.

- Cash providers that act as funding sources by pooling investors' assets;
- Banks and dealers that provide funding to hedge funds and other banks/dealers and participate in asset markets through several subagents, such as the prime brokerage and the finance desk;
- Hedge funds and other asset managers that participate in asset markets and may require funding.

As funding, collateral and securities flow through the system, they are not simply shuffled from one institution to another – the institutions take the flows and transform them in various ways. For example, credit quality changes as funding moves from the cash providers through prime brokers to hedge funds.

5.3.4 Stress testing

Financial networks are dynamic. As such, the ABM's framework is ideal for exploring the dynamic of the financial network and examining how stresses can spread. Though financial networks can manifest stability during typical day-to-day levels of risk, it is difficult to infer their reactions to sudden shocks. The network diagrams in Graph 15 illustrate how an initial shock propagates and leads to a series of sequential dynamics which impact the liquidity, leverage and allocations of the agents.

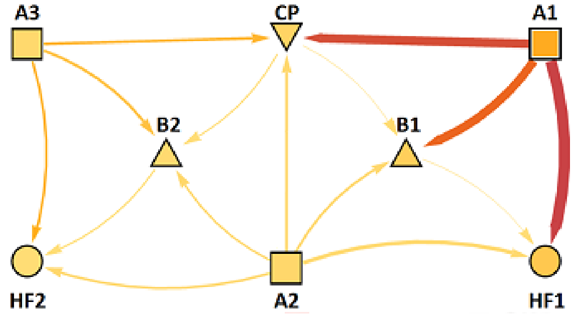
In the progression depicted in Graph 15, the solid fill within each of the nodes shows the agents' relative capital through the course of the scenario. The shrinking of this solid area within the node is proportionate to the decline in capital for the hedge funds and banks/dealers, the reduction in funding for the cash provider and the drop in prices of the assets. If the node is empty, then that agent has defaulted. Similarly, the width of the inter-node edge will increase. The colour of the edge in Graph 15 shows the intensity of the interaction in the current period – a darker colour means greater intensity or a change in the system relative to other runs and periods.

Progression of ABM simulation

Graph 15

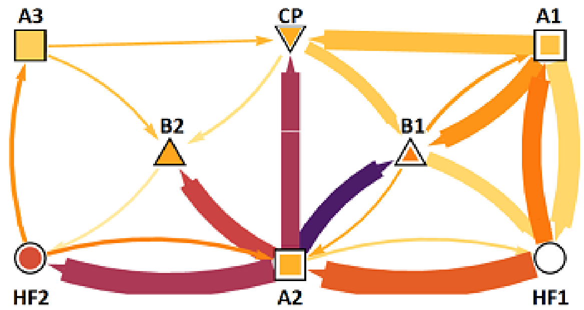
Period 0

Asset 1's (A1's) price declines sharply. Because Bank/Dealer 1 (B1) and Hedge Fund 1 (HF1) hold A1, they face losses due to the shock. The Cash Provider (CP) is also affected because the value of collateral declines. In a static stress test, the analysis ends at this point.



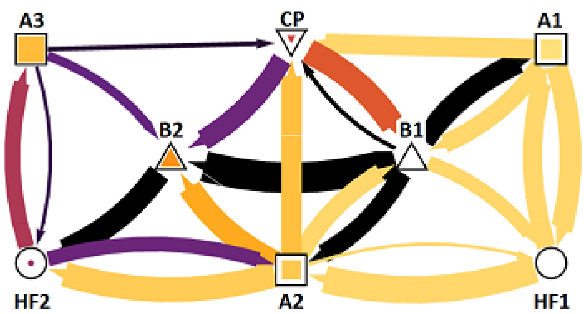
Period 2

B1 and HF1 must sell assets to cover losses on A1. They sell A1 and A2, causing a drop in the price of A2. This in turn affects other agents with holdings in A2, in particular, B2 and HF2. CP1 is affected because it holds collateral in A2 as well as in A1.



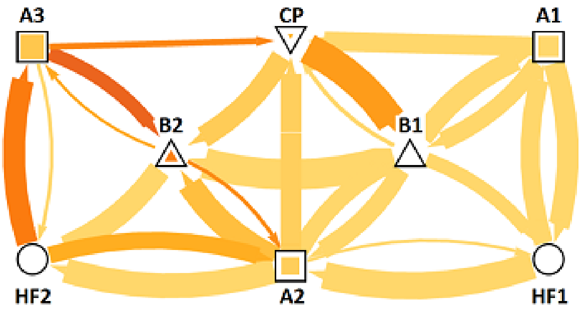
Period 4

The propagation from the shock leads to a default of HF1 and B1. Credit exposure that B2 has to B1 spreads problems through the credit channel. The drop in A2 affects HF2, and its forced sale spreads the shock to A3. Note that no firms holding A3 also hold the asset that was originally shocked, A1, but they have losses because of contagion. CP markedly reduces its funding due to the drop in the value of its collateral.



Period 6

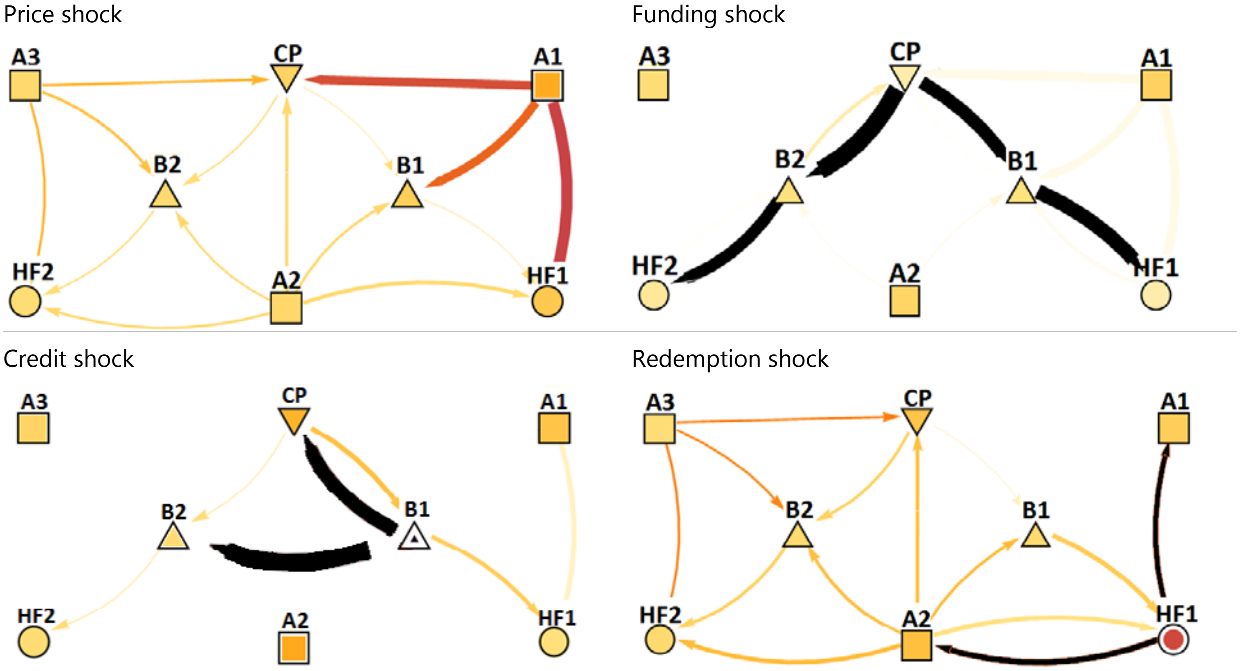
The system finally settles down with funding all but shut off, and both hedge funds and B1 in default. A2 ultimately has a greater price drop than A1, the shocked asset.



Graph 15 shows the progression of one simulation of the ABM over time. The simulation is based on 1,000 runs of the model. The graph shows a simplified setup with two banks/dealers, two hedge funds, three types of assets and one cash provider (denoted in the graph as CP). In Graph 15, Bank/Dealer 1 (B1) and Hedge Fund 1 (HF1) hold equal weights in Asset 1 (A1) and Asset 2 (A2). Bank/Dealer 2 (B2) and Hedge Fund 2 (HF2) hold equal weights in Asset 2 (A2) and Asset 3 (A3).

The model is designed to be applied in a wide range of stress scenarios beyond price shock, such as reductions in funding by cash providers, a downgrade of banks'/dealers' credit rating, or a redemption shock to hedge funds. Graph 16 illustrates each of these sources of an initial shock in the network diagram, demonstrating how they have notably different origins. This flexibility makes the ABM ideal for creative stress testing and for exploring the weakest links and bottlenecks in funding flows.

Network view of initial shock propagation Graph 16



Conclusion

Since the 2008–09 financial crisis, supervisors have made substantial progress in strengthening their ability to critically evaluate the resilience of banks. However, the real-world examples of stress tests in Iceland, Ireland and elsewhere, which sounded no early warnings, should continue to give us cause for reflection. Inadequate focus on certain risks – including liquidity risk and contagion risk – could retard the usefulness of supervisory stress tests and potentially lead to a false sense of security. Thus, additional work by supervisors on these risks can be a key complement to the standard bottom-up supervisory stress testing.

As summarised in Table 1 of Section 1.1, the work stream has sought to present some ideas to help supervisors enrich their suite of stress testing approaches with a view to considering a broader range of stress channels, liquidity and solvency interactions as well as potential systemic feedback effects. This work can help supervisors move closer to a general equilibrium understanding of how stress scenarios might affect their banking sector, and indeed their financial sector, more holistically. However, important areas remain in need of substantial additional research, most notably estimating the evolution of banks' balance sheets under stress and modelling feedback between the financial sector and the macroeconomy.

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Appendix A – Summary of supervisory models with liquidity and solvency interactions and systemic risk feedback effects

I. Central Bank of the Republic of Austria (OeNB) model

The Austrian solvency stress test is based on the constant balance sheet assumption. It covers all domestic banks on a consolidated basis (ie including fully consolidated foreign subsidiaries, which effectively equals the material central, eastern and south-eastern exposure of Austrian banks) within a common International Monetary Fund (IMF) style balance sheet approach, which combines central scenarios and various sensitivity analyses. The tests are mainly based on regulatory reporting data including granular data from the Austrian central credit registry for the assessment of credit risk.

The liquidity component calculates a cumulated counterbalancing capacity after stress. Supervisory liquidity stress tests face the following main challenges: (i) data availability, (ii) parameter uncertainty, (iii) interdependence between solvency and liquidity stress, (iv) the role of the central bank. The OeNB has developed methods and tools to address these challenges.

The liquidity stress test covers the largest 29 Austrian banks on a consolidated/subconsolidated basis with a cash flow-based methodology including security flows (see Schmieder et al 2012)). Structural parameter uncertainty, which is inherent to liquidity stress tests, is addressed via a set of embedded scenarios constructed in a hierarchy of severity. In addition, the liquidity stress test aims at ensuring that banks internalise the negative externality associated with individual banks' liquidity problems and at avoiding the moral hazard problem associated with implicit liquidity guarantees provided by central banks. Therefore, the scenarios foresee three distinct, but embedded, approaches to the counterbalancing capacity differentiated along the assumed roles of central banks under liquidity stress. The calibration of parameters draws on a documented collection of extensive case studies, literature surveys, supervisory experience in a number of countries and historical data.

Credit/liquidity interactions

Particular attention is paid to the interdependencies between solvency and liquidity stress – solvency stress can have a pronounced impact on the banks' liquidity situation. However, the latter usually also affects solvency, which in turn can lead to a vicious circle. In addition, both solvency and liquidity stress at individual banks can lead to contagion across banks. The simultaneous interdependence of solvency and liquidity risk and cross-bank contagion are hard to model in an applicable tool. The OeNB approach rests on their ordering. At first, the results of the effects of the solvency shock feed into the liquidity stress test. Then, the latter feed back into the solvency stress test after the first period (eg one quarter). At this point in time, a network-based contagion analysis captures second-round impacts within the Austrian banking system. Based on exogenous LGDs (Furfine (2003)), the impact of direct solvency stress at each bank on other banks is simulated. At the end of the second period, the results of the (enhanced) solvency results are again integrated into the liquidity stress test. The results of the latter then feed back into the solvency stress test and the contagion model. Currently, the working prototype operates with a one-year stress test horizon, with one solvency-to-liquidity, liquidity-to-solvency and contagion loop.

Solvency to liquidity

The impact of solvency stress test results on the liquidity stress test operates via four channels: (i) the macro-to-PD impact of the solvency stress test is mapped on banks' credit claims deposited at the OeNB, which impacts the respective haircuts and reduces the counterbalancing capacity; (ii) the NPL effect is mapped on expected inflows from performing loans to non-banks, which reduces cash inflows; (iii) furthermore, the results of the solvency stress test affect expected inflows from paper in banks' own maturing portfolios, which also decreases cash inflows; (iv) in a liquidity stress test over a one-year horizon, all banks are initially assumed to be shut out of funding markets, but after one quarter, general uncertainty is assumed to decrease and markets start to differentiate across banks: Based on the stressed CET1 ratios, some banks regain market access. The calibration is based on the empirical analysis of EA data.

Regarding (i), the migration of credit claims pledged at the OeNB across credit quality steps (and, thus, haircut categories) is derived from detailed bank-level collateral data. The model assumes that credit claim volumes are identically distributed across the respective PDs in each credit quality step. An increase in PDs shifts the PD range for each credit quality step upward, so that, for example, the distribution of credit quality step 2 credit claims would shift from a PD range of 0.04–0.1% to 0.06–0.12% and one third (0.02/(0.1-0.04)) of credit claims would be shifted into credit quality step 3. Thus, the haircuts on these credit claims would increase in accordance with the Eurosystem's haircut matrix. However, in the data template, of which the liquidity stress test is based on, all collateral pledged at the OeNB is aggregated in one item. Thus, we need to derive a weighted composite haircut for the entire collateral. This composite haircut is calculated in three steps: First, we volume weight haircut increases. Second, we sum across these weighted haircuts to derive a weighted average haircut increase for loans. Finally, since not all collateral consists of loans, we weight the increased composite haircut for loans by the share of loans in each bank's collateral pool. This composite haircut is then applied to the respective lines in the liquidity stress test to derive the decreasing liquidity generation capacity under interaction channel (i). This exercise needs to be rerun for different approaches to the role of the central bank in each scenario. The calibration of (ii) is a direct output of the solvency stress test rescaled to the appropriate liquidity stress test time horizon. The calibration of (iii) is more demanding, since the composition of banks' maturing assets in their own portfolios is not reported. It is proxied by the composition of banks' pledged liquid collateral. The approach to the interaction between a bank's expected future solvency and its access to funding markets is inspired by the dynamics observed in the ABCP market during the financial crisis (Covitz et al, forthcoming). Initially, issuance markets (secured/unsecured, short- and long-term) are closed for all Austrian banks in the sample. After the first quarter, uncertainty is reduced and investors can distinguish between very stable and less stable banks. We calibrate that distinction based on the results of the solvency stress test after six quarters. So, we assume that investors are forward-looking and use similar models to the solvency stress test to assess expected future solvency, and that they arrive at similar conclusions. An empirical basis for the calibration is work in progress.

Liquidity to solvency

The liquidity to solvency link focuses on two channels: (i) a cost of funding shock, and (ii) asset fire sale losses. Both feed into solvency stress tests via P&L effects. The cost of funding shock is modelled as a market shock that affects both retail and wholesale deposits and new issuances. The latter play a minor role, as most banks are assumed to be shut out of issuance markets. The shock is calibrated based on historical data for Austrian banks. In addition, we allow for some pass-through to new loans. All calibrations are complemented by sensitivity analysis around point proxies.

Asset fire sales

The asset fire sale losses capture contagion through common exposures via price and market liquidity impacts on banks' counterbalancing capacity and their P&L. They are calibrated based on the haircuts in the stress test plus the solvency shock that feeds into haircuts via the migration matrix of credit claims pledged at the central bank. The impact of asset fire sales is taken into account in the solvency stress test as "volume effect" in, both, risk-weighted assets and valuation losses. Unlike the funding cost shock, which is a market shock, the losses due to asset fire sales are bank-specific. If a bank does not have a cumulated net funding gap over the stress horizon, it does not have to sell liquid assets and, hence, faces no losses from asset fire sales. Similarly, if its cumulated net funding gap over the respective horizon is smaller than its cash position (including drawable central bank reserves), for which the haircut is zero, it incurs no losses due to asset fire sales.

The empirical evidence regarding bank behaviour in asset fire sales is inconclusive in this respect. There are papers that find that banks sell liquid assets first, to minimise immediate losses or even post gains on flight-to-quality assets in their counterbalancing capacity (Boyson et al *(*2012)); others argue that banks sell illiquid assets first, because credit-sensitive capital requirements can result in an improvement of their capital position while fair value accounting ensures that losses are profit and loss effective irrespective of the actual sale (Merrill et al (2012)). Therefore, the OeNB approach can be seen as treading middle ground until further evidence becomes available.

Network components

Finally, a contagion analysis is conducted that studies the impact on solvency – including liquidity effects – in a classic network model. The network takes into account all net exposures among Austrian banks (including secured and unsecured money market funding, bonds and participations/equity holdings outside the trading book). The default threshold is a CAR of 8% of RWA. Contagion is measured as incremental capital shortfall of defaulted banks in the contagion analysis relative to the direct solvency and liquidity stress effects. Potential contagion due to liquidity shocks is not explicitly modelled in a network model (Schmitz (2013)). The scenario design aims at including these second-round effects based on the results of previous studies of EU banks' liquidity stress tests and contingency funding plans (ECB (2008)) and concerted rounds of common liquidity stress tests conducted by the Eurosystem's Banking Supervision Committee (BSC (2009)).

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II. Bank of Canada stress test model

The Bank of Canada has developed its own suite of analytical tools – the Macro-Financial Risk Assessment Framework (MFRAF) – to stress-test the balance sheets of major domestic banks for their solvency risks (ie top-down stress test). More importantly, the MFRAF also takes into account funding liquidity risk, as well as systemic risk stemming from spillover effects through bilateral exposures between banks.

Key features of MFRAF

It is worth emphasising that the MFRAF goes beyond existing models by providing a microeconomic foundation for the behaviour of banks' creditors. As observed during the recent financial crisis, banks' creditors may refrain from rolling over their short-term claims if they have serious concerns about the quality of a bank's assets, and thus its future solvency. For this purpose, the MFRAF takes into account banks' liquidity profiles, ie their holdings of liquid (and illiquid) assets as well as their reliance on short-term funding and the potential for asset fire sales when several banks are forced to liquidate similar assets at a discount to cover for a liquidity shortage.[60]

The MFRAF operates as a sequential framework with three distinct modules (Graph A.1 sketches the basic structure of the MFRAF).

1. First, banks' balance sheets are made subject to adverse macro shocks, leading to credit losses.
2. Secondly, depending on the severity of the credit losses, funding liquidity risk may materialise. The reason for this is twofold.
   (a) First, a bank's creditors may have pessimistic views on the bank's future solvency in light of the macro shocks and their expected impact in terms of losses, and decide to not roll over their claims on maturity.
   (b) Second, under adverse market conditions with large asset fire sale discounts, the liquidity value of the bank's assets may be insufficient to meet the maturing claims, thus subjecting the bank to rollover risk.

   The balance sheet liquidity (λ) in MFRAF is defined as

$$\lambda = \frac{\text{liquid assets} + \text{fire sale discount} \times \left(\text{illiquid assets} - \text{credit losses}\right)}{\text{maturing liabilities}},$$

   captures the influences of credit risk on liquidity risk and also how creditors' views on fire sale discounts influence a bank's liquidity.

   - When $\lambda>1$, there is sufficient liquidity to meet the claims of maturing liabilities and consequently there is no run.
   - However, for $\lambda<1$, there is a positive probability of a run.[61]

[60] Formally, we adapt the theoretical model of Morris and Shin (2009), who employ a coordination game setup to model the decision of bank creditors to roll over their claims or withdraw. By employing techniques from the literature on global games, one derives a unique run threshold for the creditors.

[61] A detailed account of the model is provided in Gauthier et al (2010).

Moreover, market conditions are dynamic, with the fire sale discount becoming more penalising following a run on one bank, thereby exacerbating the rollover risk for other banks.

3. In the third and final module of MFRAF, the risks to individual banks may be amplified through interbank spillover effects. A bank with a serious capital shortfall may not be able to fulfil its obligations towards other banks, imposing counterparty credit losses on them and potentially leading to the default of these other banks.

Schematic overview of the MFRAF — Graph A.1

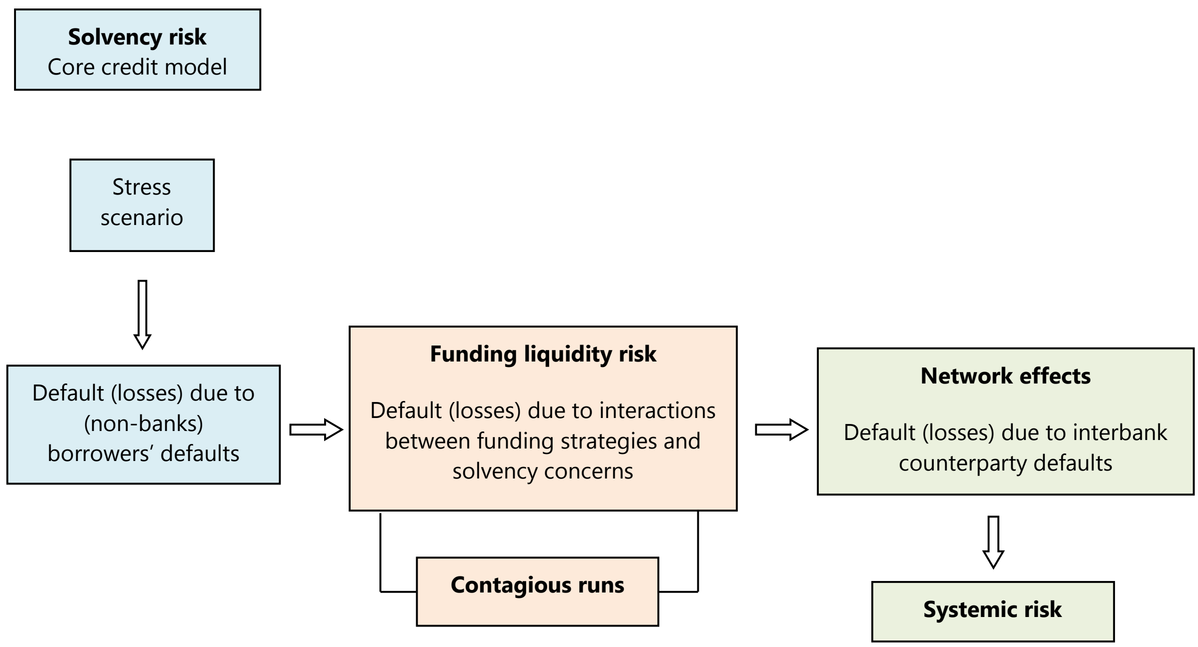


Table A.1 summarises the impact (positive or negative) of increases in the degree of various factors affecting the solvency risk, funding liquidity risk and interbank spillover risk. A higher level of capital, for example, would decrease solvency risk, while less reliance on short-term funding would reduce funding liquidity risk.

Impact of an increase in key factors affecting risks considered in the MFRAF — Table A.1

	Solvency risk	Funding liquidity risk	Interbank spillover risk
Macroeconomic shocks	+	+	+
Reliance on short-term funding		+	+
Discount on illiquid assets		+	+
Size of interbank exposures			+
Holdings of liquid assets		-	-
Capital	-	-	-

Note: The + (-) sign represents an increase (decrease) in risk.

Data used in MFRAF

Running the MFRAF requires detailed bank balance sheet information that is derived from several sources. First, for the solvency module, we need to determine banks' risk-weighted assets, income generated by banks under stress, and capital levels. These data are typically taken from what banks report in the bottom-up exercise.[62] Second, we obtain the liquidity and maturing claims profiles of banks from the Net Cumulative Cash Flow (NCCF), the OSFI's monitoring metric, which are collected on a monthly basis. As such, the balance sheet we construct for each bank is static and does not endogenously evolve over the stress horizon. The starting point for the fire sale discounts is modelled via expert judgement.[63] However, the creditors' beliefs about the possible haircuts evolve endogenously through a process of Bayesian updating. Finally, the interbank data are directly reported by the banks on a monthly basis via the Interbank and Major Exposure Return regulatory filing.

References

Gauthier, C, Z He and M Souissi (2010): "Understanding systemic risk: the trade-offs between capital, short-term funding and liquid asset holdings", Bank of Canada, *Working Paper 2010-29*.

Morris, S and H S Shin (2009): "Illiquidity component of credit risk", Princeton University, mimeo.

III. Netherlands Bank Liquidity Stress-Tester

The Liquidity Stress-Tester model developed by the Netherlands Bank (Van den End (2010, 2012)) is a top-down model that is run with bank-level data, ie supervisory data from the Netherlands' prudential liquidity report and Basel III metrics. Monte Carlo simulations produce the liquidity ratios after the first- and second-round effects of a stress scenario (ie liquidity buffers in 2010 version and LCR, NSFR in 2012 version). The 2012 version also includes a reaction function of the central bank, by which the effects of unconventional monetary policy measures on banks' liquidity positions can be simulated. The model does not include a network module, but contagion between banks results from the effects of balance sheet adjustments on prices and volumes in the markets and funding channels to which banks are exposed.

Liquidity/solvency interactions

The model takes into account the interaction between the market and funding liquidity risks of banks. Stress scenarios are composed by stochastic simulations of univariate shocks to market and funding liquidity risk exposures. Credit risk and bank solvency are not modelled explicitly, but stress scenarios that drive the liquidity values of assets and liabilities indirectly affect the value of bank equity. A reverse

[62] A current active area of research is to project these quantities using internal models. BoC staff has developed empirical models of net interest income and non-interest non-trading income where revenue drivers are macro-financial variables included in the stress scenario. This allows the results reported by banks to be checked, and overwritten where deemed desirable (eg if banks report income dynamics that seem too optimistic given the stressed conditions).

[63] For example, one could use the haircuts prescribed in the liquidity coverage ratio (LCR) as a viable starting point.

link between solvency and liquidity runs through the design of scenarios, which could include shocks on credit markets that affect the liquidity value of bank assets.

Second-round feedback effects are determined by the number and size of reacting banks and the similarity of their reactions. Bank reactions are based on an ex ante-specified reaction rule. The elasticities of spillover effects of banks' reactions are based on (subjective) assumptions, where possible derived from literature. Bank reactions lead to portfolio rebalancing across the maturity and risk dimensions and act as an amplification mechanism between solvency and liquidity risk.

Fire sales/feedback loops

The model includes both market-wide effects resulting from banks' behavioural responses. This creates various channels through which liquidity risk affects solvency and vice versa. Responses in terms of asset sales – due to liquidity stress – will impact on banks' solvency effect if assets are sold at fire sale prices. The central bank reaction (ie asset purchases) can limit the price effects of fire sales and support the solvency of banks. Another channel runs from liquidity risk to credit supply. If banks curtail lending to the real economy, it amplifies the potential solvency losses in bank loan portfolios. The model also allows for idiosyncratic reputation effects resulting from banks' balance sheet adjustments. Its signal affects a bank's reputation and thereby the franchise value of the bank.

References

Van den End, J W (2010a): "Liquidity stress-tester: a model for stress-testing banks' liquidity risk", *CESifo Economic Studies,* vol 56 (1), pp 38–69.

——— (2012), "Liquidity stress-tester: do Basel III and unconventional monetary policy work?", *Applied Financial Economics*, vol 22, pp 1233–57.

IV. Bank of Mexico stress testing model

Under the stress testing framework of the Bank of Mexico, a distribution of losses for the whole banking system can be obtained. This distribution of losses plays an important role in developing relevant measures of systemic risk.

The framework takes into account several important aspects associated with systemic risk: an initial macroeconomic shock that causes initial losses, potentially weakening some institutions to the point of failure; a contagion process between banks; and the resulting final losses to the financial system as a whole. Once the distribution is estimated, standard systemic risk measures can be obtained, focusing on the tail of the distribution (where the catastrophic or systemic events are located).

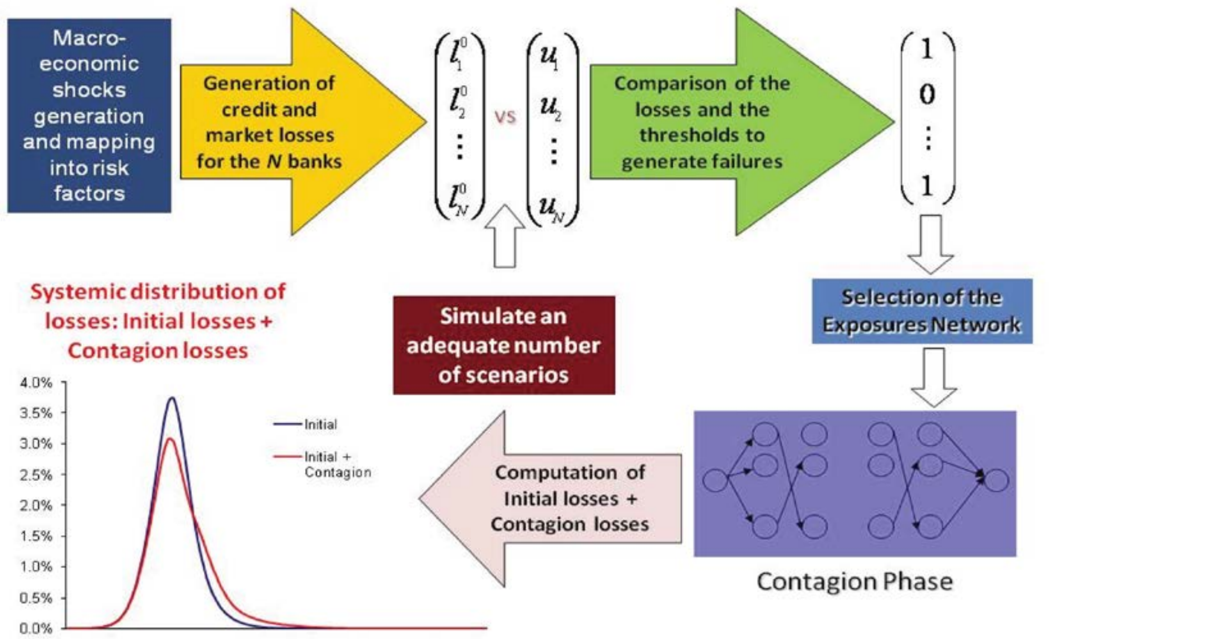
By using the proposed framework, stress tests can be performed in a coherent way, including second-round effects such as losses due to contagion through the interbank market. Additionally, the evolution of certain measures, such as the conditional value-at-risk (CVaR), can be tracked in order to determine whether the system is becoming more risky or fragile. Likewise, losses due to contagion can be isolated from the final distribution of losses to assess whether the system is more prone to experiencing greater difficulties due to contagion for a certain period of time.

The Bank of Mexico's approach is a bottom-up one, which is possible because the bank possesses detailed information on each bank. Because all exposures are known to the central bank, and thanks to the size of the Mexican banking system, computer simulations can be performed in order to estimate the distribution of losses for the banking system as a whole. However, this requires generating joint losses for market and credit risk. The simulation model generates consistent macroeconomic scenarios by preserving the interdependence between the risk factors, which will have an effect on both market and credit portfolios. For example, an increase in interest rates would affect the distribution of market losses and lead to an increase in the number of defaults in the credit portfolio. Finally, banks would suffer further losses after the second-round effects (due to contagion).

There are several ways in which the link between losses and the real economy can be made. Some approaches can be more theoretically sound or robust than others, ranging from highly sophisticated dynamic general equilibrium models to relatively simple statistical models. Considering the availability of information and the trade-off between tractability and predictive power, a structural Vector Autoregressive (VAR) model was chosen to capture the relationship between economic variables and losses. Despite its limitations, it remains a suitable approach to model the short-term effects that a macroeconomic scenario can have on the credit and market portfolios of banks; the central bank has enough data to accurately compute the impact of these shocks on the market portfolios and can even use this data to make projections on a bigger set of variables whenever necessary (in which case, using a VAR model allows parsimony to be retained).

An extension to the VAR that has been explored in order to avoid over-parameterisation, especially when the number of time series grows large, consists of using a Bayesian VAR (BVAR) with a modified Minnesota prior. This kind of VAR model has been shown to avoid over-parameterisation. Structural and restricted VAR models were ruled out because they might miss some concealed dependence relations.

Schematic overview of the MFRAF — Graph A.2



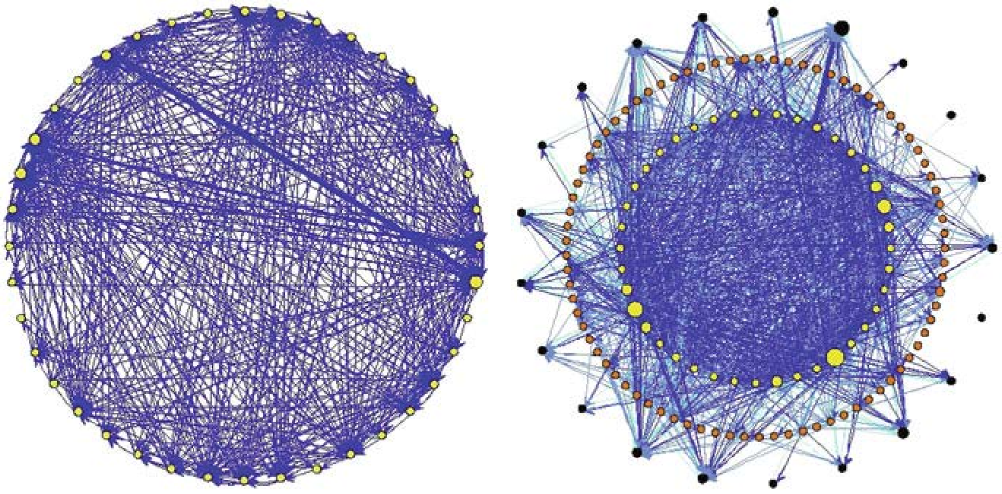
Extending the exposures network

Under this approach, banks and brokerage firms are shocked at the beginning of the simulations and, afterwards, contagion through direct exposures is evaluated. The initial shock can be obtained from any scenario, stressing whichever variables one wants.

The interbank network is modelled using a weighted digraph, where financial institutions are represented by nodes N = {1, 2, 3 . . . n} and bilateral exposures are represented by the matrix W, where the (i,j) entry, wij, represents an exposure from bank i to bank j (and thus the weight of the arc from i to j in the graph). The weighted digraph can be visually represented with a network. Graph A.3 shows two different exposures networks: Graph A.3 (left panel) shows an interbank exposures network and Graph A.3 (right panel) shows an extended exposures network including more financial intermediaries: brokerage firms, investment funds, pension funds and international banks. Graph A.3 (right panel) shows banks in yellow, domestic financial institutions other than banks in orange and international banks in black.

Contagion is modelled as follows: after the initial losses (generated by the economic scenario) are applied to each bank and brokerage firm, the regulatory capital of each affected institution is computed to verify whether the institution is still solvent. Mexican regulation establishes that the regulatory capital of banks must not be lower than 8%. If a bank's capital ratio falls below this level, measures are then taken by the Mexican Deposit Insurance Corporation and the central bank; if the capital ratio of a bank falls below 4%, the bank is formally declared bankrupt. Similarly, for a brokerage firm, if its capital consumption index exceeds 100%, measures are taken by the Mexican financial authorities; if its index exceeds 120%, the firm is formally declared bankrupt.

Exposures networks — Graph A.3



(a) Interbank exposures **(b)** Interfinancial exposures

Further improvements to the framework

It is important to note that, under the current contagion model, only solvency is taken into account when testing the resilience of the system. However, banks can also fail because of liquidity shortages and credit problems. Another problem arises due to the term mismatch between credit and market risk (credit takes longer to respond to external shocks). In addition, the current model considers a static network. Consequently, as further work, it is important to consider a dynamic model integrating credit risk, liquidity risk and market risk. Concerning liquidity risk, only a few efforts have been made to incorporate it with existing frameworks, which would represent an important and realistic extension.

V. Central Bank of Norway's stress testing model

The banking model is part of a stress test framework that also consists of a macroeconomic model with a financial sector and sectorial PD models. The banking model is used for several purposes:

- Give forecasts of banks' return and CET1 ratio given a reference path for macro variables.

- Analysing new regulation, like the effects of changes in capital requirements.
- Stress testing; bank behaviour under stress; feedback to the macro model under stressed conditions.

The model is a flexible framework for quantifying effects of regulation and macroeconomic shocks on banks' balance sheets, allowing for a dynamic response from the banks. Banks in the model will adjust lending rates and credit growth. The banks' behaviour is controlled by two factors:

- A target for long-run return on capital;
- A target for the core tier 1 (CET1) capital ratio.

Banks are assumed to prioritise lending growth. On the margin, banks will prioritise lending to households over lending to the non-financial corporate sector. However, banks' credit growth is upwards constrained by the credit growth we obtain from the macro model. Remaining free capital will be paid out as dividends. In an alternative version, banks first prioritise paying dividends as a fixed amount of net profits, and then maximise lending. In stress, dividends are set to zero. The banks will try to adjust their lending margins to obtain a target equity return (set to 12% in equilibrium).

Data

Banking data are quarterly, consolidated bank group data from SNL Financial. Macro scenarios are estimated using the Central Bank of Norway's monetary policy core DSGE model, NEMO. This model includes a financial sector, a credit market and a housing market. The macro model is explicit in its assumptions about banks' lending rates. Sectorial PD models run as satellites to the macro model. A markup on banks' funding over money market rates is calculated by the market operations department.

Decision time line

The model updates the balance sheet quarter by quarter.

- Banks' funding rate is determined based on input on money market rates, the markup on market funding due to higher rollover costs, and estimated rates on customer deposits.
- Each bank calculates the lending rate needed to reach a target for return on equity. In the calculation, the bank will input actual assets and liabilities at the end of period t-1, expected losses in period t, expected funding costs in period t and expected costs and other income in period t. Expectations are backward-looking. The bank's flexibility to adjust rates is a function of competition, regulation and the time structure of lending:
    - The aggregate lending rate can only be adjusted up by 25 bp per quarter
    - The maximum interest rate hike for a bank is dependent on what happens at the other banks. We can impose different rules, like maximum hike is equal to the bank with the minimum hike, maximum hike is equal to the hike at the largest bank, or maximum hike is equal to the bank with the largest hike.
    - The ability to set rates will also depend on whether the central bank's deposit rate changes or not. Historically, it has been easier for the banks to change rates when they do this at the same time as the central bank.
- Credit losses are calculated based on changes and the level of sectorial PDs, and assumptions about LGD ratios and realised return on other assets and taxes. Losses on assets held mark-to-market are estimated based on changes in interest rates and stock prices.
- We can now obtain the period t financial result after tax.

- In stress, average risk weights will be adjusted to reflect migration of assets to higher risk classes.
- Given the last period CET1 ratio and current and future regulation, banks set a target for CET1.
- The bank can now either pay out a certain amount of net profits as dividends, or it can first maximise lending, and then decide on the level of dividends. Dividends never exceed the level of net profits.
- Depending on the assumptions about dividends, banks calculate the optimal level of risk-weighted assets (RWA). Operational RWA are supposed to react to changes in income. Market-based RWA are constant relative to counterparty RWA.
- The banks try to adjust their current loan portfolio to meet the new target level of RWA.
- Banks will optimise their lending portfolio given rates of return and risk weights on different types of assets. The adjustment is made under restrictions:
  - The marginal risk weight on household loans is set to 40%, and the marginal risk weight on loans to firms to 80%.
  - Growth in household debt is determined by the rate in the macro scenario ("demand"). In the model, it will therefore be exogenous.
  - The "available" RWA after having supplied household lending gives us the potential supply of loans to non-financial firms. However, we assume that banks' aggregate lending to firms cannot fall by more than a given maximum per quarter, and that lending cannot increase faster than the increase in demand for loans (given from the macro model). If any of these restrictions are binding, the actual core tier 1 ratio will differ from the target core tier 1 ratio.
- Unless we assume liquidity stress, banks will adjust senior debt so that assets equal liabilities.

Liquidity stress

The model includes an option of liquidity stress. Based on the above analysis, we can calculate the banks' need for new financing in a given quarter. In addition, we find the expected refinancing need based on the volume of bond issues that are terminating in the given quarter. From this we can calculate the net need of new financing. In liquidity stress, banks are no longer able to find new market financing. If they have a negative net cash flow, they must liquidate parts of the market portfolio. The liquidation is done at a discount. The difference between the liquidation value and the market value will add to the losses in the following period, thereby increasing the strain on the bank.

Interaction between macro model and bank model

The feedback process between the macro and micro models follows this procedure:

- We obtain macro variables and credit growth from the macro models.
- We then run the bank model, obtaining banks' lending rates, funding costs and credit growth to non-financial enterprises.
- The level of these three variables will be compared with the assumptions in the macro model.
- If deviations are substantial (eg if the credit growth to non-financial enterprises is much higher in the macro model than in the bank model, or if interest margins differ much), we will adjust the assumptions in the macro models. We will then run the macro model again under new assumptions.

VI. Bank of Korea funding liquidity contagion module

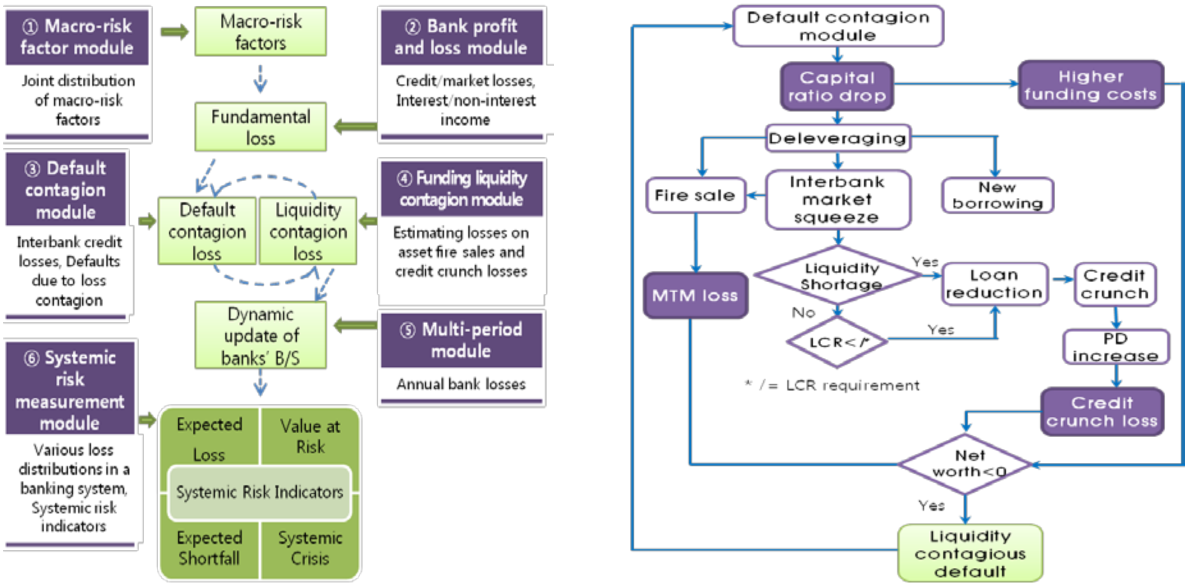
Overview

Systemic Risk Assessment Model for Macroprudential Policy (SAMP) is an integrated model which enables us to conduct the measurement of various kinds of risks, the probabilistic assessment of systemic risk and macro stress testing of the banking system. It models not only the first-round effects of macroeconomic shocks, but also the second-round effects through interbank contagion, fire sales, credit crunches and deleveraging. It consists of six modules; namely, a macro-risk factor module, a bank profit and loss module, a default contagion module, a funding liquidity contagion, a multi-period module, and a systemic risk measurement module.

The funding liquidity contagion module assesses the funding liquidity risk of the banking system based upon two main factors: (i) the interactions between solvency risk and liquidity risk, and (ii) the interconnectedness of the banking system. This module incorporates the process of funding liquidity risk contagion whereby funding liquidity risk driven by solvency risk propagates throughout the banking system as a whole through asset fire sales and liquidity withdrawals, which leads again to solvency risk (interaction between solvency risk and liquidity risk). To capture the contagion effects of interbank liquidity withdrawals, SAMP uses a network model incorporating the maturity structure of banks' assets and liabilities (interconnectedness of the banking system).

Structure of SAMP — Graph A.4

Overall structure — Funding liquidity contagion module



Source: Bank of Korea, *Financial Stability Report*, October 2012.

Structure of funding liquidity contagion module

It is assumed that a decrease in the capital ratio caused by a macroeconomic shock triggers liquidity run-offs and increased funding costs as well. In response to the liquidity run-offs, a bank hoards liquidity by selling its assets or calling in its claims on other banks, which causes a propagation of the funding liquidity risk to the banking system as a whole.

Additional funding cost: The additional funding cost resulting from a decrease in the capital ratio is estimated by assuming the funding cost of a bank as a decreasing function of its capital ratio.

Liquidity run-off: The run-off rate of banks' liquid liabilities is modelled as proportional to the decline in the capital ratio. With this function, the amounts of run-off of distressed banks are estimated.

Asset fire sale: When a bank faces a liquidity run-off, it is assumed to cope by calling in its claims on other banks and selling its external liquid assets proportionately to their share in its total liquid assets. Under this balance sheet dynamic assumption, the amount of liquid asset sales is calculated, and the mark-to-market (MTM) losses of banks are then estimated using the decrease in asset price, since the asset price is modelled as a function of the amount of asset sales.

Interbank market squeeze: The amount of interbank liquidity withdrawals is estimated through Lee's (2013) analysis of the banking system network structure, which is based on the fictitious default algorithm (Eisenberg and Noe (2001)). To conduct this estimation, an interbank exposure matrix is built with the interbank exposures and their maturity structures from the banks' balance sheets.

Liquidity shortages: A bank is considered to face a liquidity shortage if its total liquidity needs (the sum of the initial external liquidity withdrawal and the subsequent interbank liquidity withdrawal) exceed the amount of its total liquid assets. In order to evaluate the effect of liquidity regulation, especially the LCR requirement, a bank which needs additional liquid assets to meet the LCR requirement is also considered as being in a liquidity shortage even though it has a liquidity buffer. A bank suffering from a liquidity shortage in this stage hoards liquidity by selling its illiquid assets, which leads to a credit crunch since most illiquid assets are composed of loans.

Credit crunch losses: Occurrence of a credit crunch may cause banks substantial losses due to feedback effects through macro-financial linkages. A reduction in illiquid assets gives rise to a macroeconomic slowdown and a further increase in default rates, leading to additional bank losses. The feedback default rate is thus modelled as an increasing function of the amount of illiquid asset sales in the banking system as a whole, based upon which the credit crunch losses from the increased default rate are estimated.

Liquidity contagious default: When all of the losses incurred during the liquidity contagion stage – additional funding costs, MTM losses and credit crunch losses – are taken into account, a liquidity contagious default occurs if the net worth of a bank falls below the default threshold point. The losses incurred are subsequently re-estimated through the default contagion module in SAMP.

Test horizon, input data and liquidity metric

Test horizon: SAMP is based upon quarterly data. It thus estimates banks' losses and liquidity metrics for horizons longer than one quarter by updating the banks' balance sheets dynamically in reflection of the results of estimation on a quarterly basis. The multi-period module in SAMP specifies this iterating process.

Data: Most of the data used in SAMP is detailed balance sheet information obtained as supervisory information. The input data of funding liquidity contagion come from the assets and liabilities, broken down by maturity. In order to build the interbank exposure, other data such as flow of funds data and additional surveys of banks are also used. Interbank exposures are updated every quarter.

Liquidity metric: The liquidity metric of this module is the liquidity buffer, which is defined as the difference between the amount of liquidity needs and the amount of total liquid assets.

However, since the funding liquidity module is one module of the integrated model, SAMP, various liquidity risk metrics are also calculated, including loss, capital ratio and the number of bank defaults. If a macro scenario is set as the joint probability distribution of macro factors, the distribution of the metrics can also be calculated.

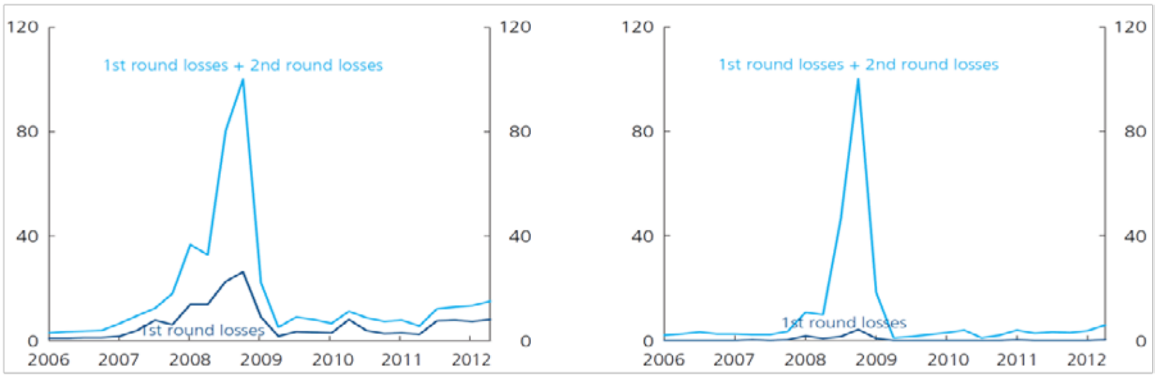
Assessment of systemic risk of Korean baking system using SAMP

Graph A.5 is the result of a systemic risk assessment using SAMP published in the October 2012 *Financial Stability Report*. In this analysis, the Expected Shortfall (ES) Index of the distressed bank ratio and the Systemic Crisis Probability Index were used as systemic risk indicators. The distressed bank ratio ES Index is an indicator showing the tail risks of the banking system, measuring changes in the distressed bank ratio that may occur with a 1% probability within one year. The Systemic Crisis Probability Index shows changes in the probability of simultaneous defaults of two or more banks within one year.

The results of the analysis show that systemic risk has declined significantly in Korea in comparison with the period around the global financial crisis. While the second-round effects are greater than the first-round effects in most periods, the second-round effects drastically increased during the global financial crisis. This result reflects non-linearity in SAMP, which is introduced to capture the amplification and propagation mechanism in the banking system of macro-risk factors as a whole.[64]

Systemic risk assessment of Korean banking system | Graph A.5

Distressed bank ratio[1] ES Index[3] | Systemic Crisis[2] Probability Index[3]



[1] Distressed banks are defined as banks with less than 8% BIS ratios. ES is an indicator that measures tail risks more conservatively than VaR. In this calculation, ES is estimated conditional on the distressed bank ratio (number of distressed banks/total number of banks) occurring with less than 1% probability. [2] A systemic crisis is defined as a situation in which two or more banks go bankrupt simultaneously. [3] The peak during the global financial crisis is set at 100 in the indices. [4] The first-round losses are generated directly by macro shocks. The second-round losses mean that bank losses were incurred due to second-round effects such as interbank contagion effects, fire sales, credit crunches and deleveraging.

Source: Bank of Korea, *Financial Stability Report*, October 2012.

References

Bank of Korea (2012): "Systemic Risk Assessment Model for Macroprudential Policy (SAMP)", *Financial Stability Report*, October.

Eisenberg, L and T Noe (2001): "Systemic risk in financial systems", *Management Science*, vol 47, pp 236–49.

[64] The funding liquidity shock (liquidity run-offs) is originated by solvency risk followed by a macroeconomic shock. Thus, the origins of shocks in the Bank of Korea's liquidity model should be regarded as the first category (macroeconomic shock on credit quality).

Lee, S H (2013): "Systemic liquidity shortages and interbank network structures", *Journal of Financial Stability*, vol 9(1), pp 1–12.

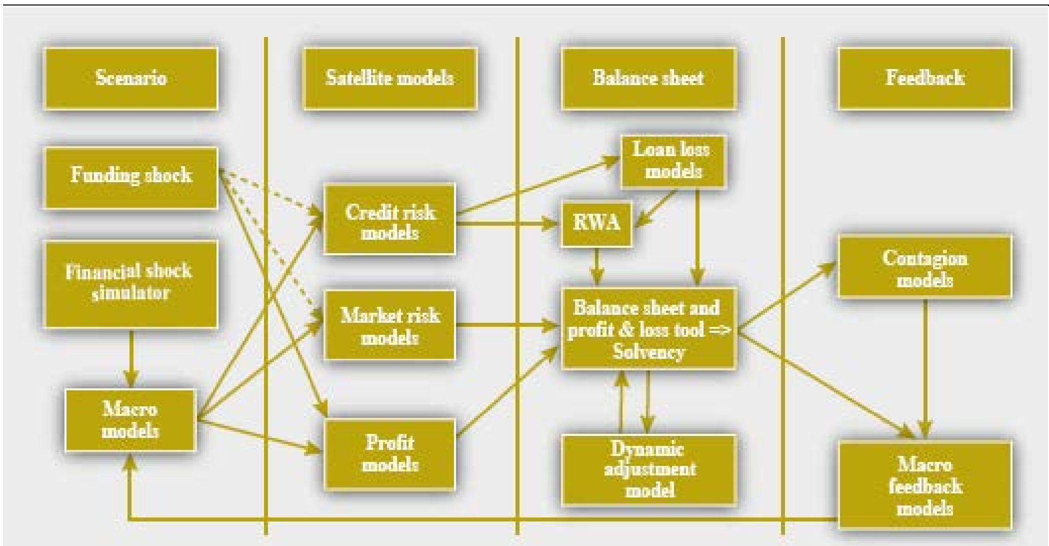
VII. ECB top-down stress testing framework

The ECB has developed a top-down macro stress testing framework that is used regularly for forward-looking bank solvency assessments (Henry et al (2013)). Macro stress testing is part of the ECB's toolkit to safeguard financial stability in the euro area. The framework will also be an integral part of the ECB's activities in relation to its future role as a single bank supervisor.

In essence, the framework is a solvency stress testing model, which consists of four pillars, namely, the macro-financial scenario design, models to translate scenarios into impacts on banks, the solvency calculation module and a module for contagion and feedback analysis. The framework is thus based on a number of different building blocks and models that are linked together consistently and dynamically to provide a flexible tool for assessing banking sector resilience against identified systemic risks (see Graph A.6).

The four pillar structure of the ECB solvency analysis framework

Graph A.6



Source: ECB.

The first pillar (scenario design) consists of the design of the macro-financial scenarios to be imposed on the banking sector. Financial shock scenarios are based on extreme tails of historical distribution of variables. Interdependencies between variables are captured by copula functions.

The second pillar (top-down satellite models) in turn consists of the modules used to translate the scenarios into variables affecting the valuation of bank balance sheet components and banks' loss absorption capacity. The ECB uses top-down satellite models for credit risk, interest rate risk and market risk (liquidity risk is not explicitly modelled).

The third pillar (balance sheet module) takes the projected profit and losses derived from the satellite models to individual bank balance sheets with the aim of calculating the resulting impact on each bank's solvency positions. This is based on a dynamic balance sheet tool so that it can apply either exogenously given or endogenously optimised paths for key balance sheet items. The tool includes an endogenous path for key balance sheet items based on banks' optimising behaviour and assumes that banks optimally restructure their assets following a risk-adjusted return maximisation programme.

Finally, the fourth pillar (feedback modules) takes the analysis beyond the first-round impact on bank capitalisation to assess what could be the derived second-round effects of the initial bank solvency impact in terms of contagion within the financial system and in terms of feedback effects to the real economy. The tools applied at the ECB for these purposes range from exposure-based interbank network models and financial account-based cross-sectoral network models to market data-based spillover models. The framework of interbank contagion includes both a mechanical and static loss-cascading mechanism, as well as more dynamic (agent-based) multi-layered network formation models. Feedback effects between macroeconomic and financial variables are analysed using DSGE models and reduced-form econometric models.

In the model framework, the liquidity element (ie higher funding costs) hampers a bank's ability to pass a solvency test, while higher collateral needs for secured funding, the closure of funding markets or the default of a bank's major liquidity providers hampers a bank's ability to maintain a certain degree of liquidity. Collateral values affect the external finance premium. The dynamic balance sheet tool can take into account the impact of any expected future capital injection (in the form of cash or marketable securities) on banks' funding volume and structure. This is particularly relevant for top-down stress test exercises in EU/IMF programme countries, where funding strains are usually high and any expected capital injection has a significant impact on the availability of funding and the ability of banks to provide credit to the economy.

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

References

Henry, J, C Kok, A Amzallag, P Baudino, I Cabral, M Grodzicki, M Gross, G Hałaj, M Kolb, M Leber, C Pancaro, M Sydow, A Vouldis, M Zimmermann and D Żochowski (2013): "A macro stress testing framework for assessing systemic risks in the banking sector", European Central Bank, *Occasional Paper Series*, no 152, October.

Appendix B – Network subgroup details

Network descriptions

Overview of the networks examined

Table B.1

Country	Type of network	Short description
Brazil	Interbank exposures	Interbank market exposures between financial institutions, both banking and non-banking, related to unsecured operations.
	Payment	Payments between banks, on their own account, taken from the Brazilian Large Value Payment System (LVPS) and aggregated for one day.
BIS	Interbank exposures	Bilateral financial system exposures on banks as given in the BIS International Banking Statistics.
Canada	Interbank exposures	Aggregate bilateral exposures between Canadian domestic systemically important banks consisting of: banker's acceptances, debt securities holdings, unsecured lending (drawn and undrawn), OTC derivatives (potential future credit exposures), repurchase agreements (before collateral) and deposits.
Denmark	Interbank exposures	Interbank loans derived from the KRONOS large-value payment system.
	Repo	Net bilateral repo exposure between Danish banks.
France	Interbank exposures	Bilateral exposures between French bank holding groups in December 2011 with values higher than 10% of banks' capital or above EUR 300 million. It is obtained from the quarterly Credit Register report.
Hungary	Interbank exposures	HUF interbank unsecured deposit transactions between Hungarian banks. All institutions and all transactions are included.
	FX swap market	All the transactions on the HUF/FX currency swap market where at least one participant is Hungarian.
Italy	Interbank exposures	Interbank unsecured market exposures (short-term loans – up to one year).
Korea	Interbank exposures	Interbank exposures with a remaining maturity of less than three months. These bilateral exposures, which include all on-balance sheet items such as deposits, loans and debt securities, are estimated using flow of funds data and a survey of bilateral interbank holdings.
Mexico	Interbank exposures	Total bilateral exposures (MX01..); outstanding deposits and loans (MX03..); and transacted deposits and loans (MX06..)
	Repo	Repo amounts lent and borrowed between banks without considering the risk mitigation associated with the collateral.
	Equity	Cross-holding of securities.
	Derivatives	Outstanding derivatives.
	Payment	Total flow of payments (MX07..); participant to participant payments (MX08..); and third-party to third-party payments (MX09..).
Netherlands	Interbank loans	Using data for the payment system TARGET2, interbank loans are inferred including all loans involving a Dutch bank.
UK	CDS	The DTCC's Trade Information Warehouse data. Includes all exposures on single name CDS contracts where the reference entity is UK-domiciled, or at least one of two counterparties is UK-domiciled. UK02 is the 30% largest in volume.
US	Payments	Fedwire large-value payment system for two time periods.
	CDS	See UK. In addition, index with a majority formed by UK firms.

Description of the metrics investigated

This section discusses the measures included in the standard output exchanged among the members of the work stream, grouped in four categories: (1) network statistics, (2) matrix similarity, (3) confusion matrix measures and, finally, (4) DebtRank-related measures. We cover each in turn.

Network statistics

Number of links	The number of undirected links in the network.
Density	The number of undirected links as a percentage of the total number of links (excluding self-loops).
Average degree	The average number of undirected links of the nodes in the network.
Median degree	The median number of undirected links of the nodes in the network.
Assortativity	The preference for a network's nodes to attach to others that are "similar". Here, similarity is expressed in terms of a node's degree. A high value means that highly connected nodes tend to be connected with other high degree nodes. This tendency is referred to as assortative mixing, or assortativity.
Clustering	A measure of the degree to which nodes in a graph tend to cluster together. In an undirected setting, this is defined as the number of closed triplets (any three nodes with links between all three) over the total number of triplets (including triplets with one link missing). This is generally defined as a Global Clustering coefficient.
Lender/borrower dependency	The average of the market share of the largest borrower or lender, respectively, over total borrowing and lending.
HHI	The average Herfindahl-Hirschman concentration index (mean and median) of both assets and liabilities. It is defined as the sum of the squared "market shares".
Core size	The percentage of banks classified as belonging to the core.
Error score	The percentage of the actual links in violation of the perfect core periphery structure.

Matrix similarity

Measures capturing the similarity between the original matrix and the estimated matrix. For all measures, lower values denote more similarity. In some cases, this means that our definition is the inverse of the customary one.

Hamming	Sum of the difference between the original and estimated *adjacency* matrices. This measure captures the number of instances where the original matrix had a link but the estimated did not (false negative), and where the original matrix did not have a link but the estimated matrix did (false positive). Range: $[0, \infty)$.
Jaccard	The inverse of the number of links belonging to both the original and estimated adjacency matrices divided by the number of links that belong to at least one of these matrices. Range: [0,1].

Cosine	The inverse of the transformation of the original and estimated □ × □ matrices into vectors of dimension □^{2}. The cosine similarity thus computes the angle between the two vectors. Range: [0,1].
Jensen	The Jensen-Shannon divergence measure compares two probability distributions. We normalise the matrices such that the sum of entries is one. Range: [0,1].

Confusion matrix measures

The error scores discussed above aggregate errors both in the core and in the periphery. Here, these are split into four subcategories. We also show four other fit measures, that is accurary, etc.:

True Positives	Percentage of links in the estimated network that are also in the original network.
True Negatives	Percentage of links absent in the estimated network that are also absent in the original network.
False Positives	Percentage of links in the estimated network that are absent in the original network.
False Negatives	Percentage of links absent in the estimated network that are present in the original network.
Accuracy	The sum of true positive and true negatives over all observations (percentage).
Top n	Top n nodes: takes the value of 1 if the vertex with the highest centrality in the original network is among the n nodes with the highest centrality in the estimated network.
Correlation	The correlation between the centrality measures in the original and the estimated network.
Overlap n	Ranges between 0 and 1 and reflects the extent to which the first n nodes in the original network match the n nodes in the estimated network (bootstrapped network). The measure is computed in the following way: $$O = \frac{\lvert V^o \cap V^p \rvert}{\lvert V^o \cup V^p \rvert}$$ where V^o is the set of the first n nodes which belong to the original network and V^p is the set of the first n nodes which belong to the perturbed network.
Shortfalls	The total funding shortfall in the interbank market due to a run-off on non-interbank deposits and liquidity hoarding by banks. We use Lee's (2012) method to estimate the funding needs.

Appendix C – Details on bank data used in the empirics of the interaction between solvency and funding costs for large international banks (Section 3.2)

In principle, each variable could have 1,998 data points. However, not every data point is available. Table C.1 gives more detail on data availability.

Data coverage

Table C.1

	Available observations per variable	Available observations in %
CommonEquityTier1_in_percent_of_RWA	1159	58.01%
CoreTier1_in_percent_of_RWA	1632	81.68%
Tier1_in_percent_of_RWA	477	23.87%
Price_to_tangible_book	1184	59.26%
Tangiblecommonequityratio	1458	72.97%
EDF_1y	1591	79.63%
EDF_5y	1625	81.33%
FVOAS_5y	764	38.24%
FVCDS_5y	1625	81.33%
Totalassets_USD	1847	92.44%
RWA_USD	1864	93.29%
Tier1Common_USD	1222	61.16%
CoreTier1_USD	1569	78.53%
Tier1_USD	499	24.97%
LoanLossReserve_in_Totalloans	1569	78.53%
Short_termdebt_in_total_assets	1565	78.33%
Loan_to_Deposit_Ratio	1719	86.04%
excessive_reserves_in_totalassets	1823	91.24%
FX_exposureliabilities_in_percent_TA	276	13.81%
NPLs	1365	68.32%
LoanLossProvisions_in_total_Assets	1839	92.04%
NetInterestIncome_in_total_Assets	1839	92.04%
NetInterestExpense_in_total_Assets	1815	90.84%
Netincome_in_total_Assets	1839	92.04%
LoanLossProvisions	1839	92.04%
NetInterestIncome	1839	92.04%
NetInterestExpense	1815	90.84%
Netincome	1839	92.04%
ER_regime	1998	100.00%
CDS_gov	1515	75.83%
Loan_growth	1997	99.95%
fitch_rating_scale	1311	65.62%
moodys_rating_scale	1395	69.82%
S_P_rating_scale	1514	75.78%

Number of banks: 54. Number of total observations per ratio: 1,998.

The distributions of the banks' CDS_5y and EDF_5y are presented in Graph C.1. The borders of the boxes on the upside and on the downside indicate the first and the third quartile. The black line in the box indicates the median. The bars above and below the boxes are the so-called whiskers. The whiskers indicate the largest and the smallest values of the sample, if these values do not deviate more than the 1.5-fold of the interquartile range to the median. The interquartile range is defined as the distance from the first to the third quartile. In the event that observations deviate more from the median than the 1.5-fold interquartile range, the whiskers denote the 1.5-fold interquartile range to the median in the respective direction. The small points above and below the whiskers denote observations that are farther away to the median than 1.5-fold of the interquartile distance. For the CDS data, the first quartile is located at 45 bp, the second quartile is located at 131 bp and the third quartile is located at 249 bp.

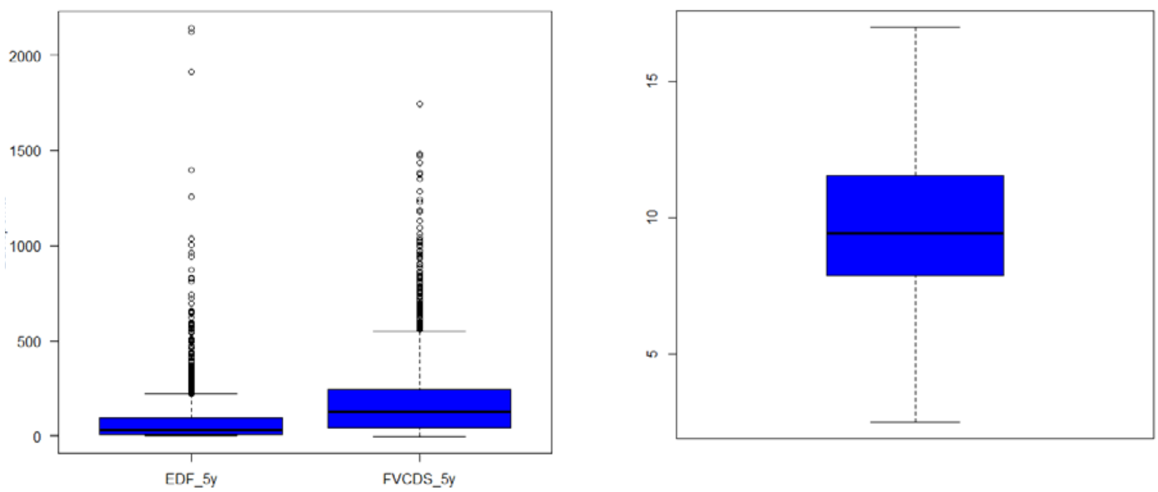
The narrow boxes in the left panel of Graph C.1 suggest that the CDS and EDF can vary significantly.

The right panel of Graph C.1 displays the distribution of the core tier 1 ratio (CT1). In this graph, extreme observations are excluded (but they are included in the estimations if the data quality check was successful for the individual observation). For this ratio, the first quartile is 7.89%, the third quartile is 11.55%, the mean is 10.5% and the median is 9.42%.

Bank EDF, 5y CDS and CT1 ratios Graph C.1

Box plot of bank EDF and 5y CDS | Box plot of bank CT1 ratios

Basis points | Per cent of RWA



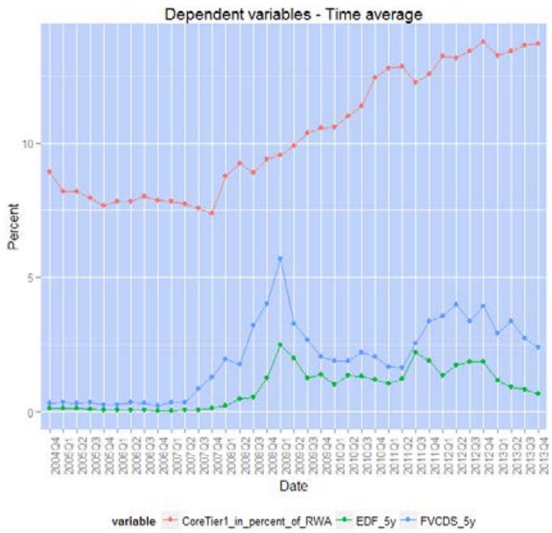
Sources: Various central banks and regulatory agencies (right panel); Moody's (left panel).

The next graphs display the evolution of the averages across banks of CT1, EDF_5y and CDS_5y over time. These three variables feature as dependent variables in the model estimations. The top-left panel of Graph C.2 plots the averages across all banks in the sample, while the top-right panel displays averages for Canadian and US banks only. The bottom panels show the averages over time for European banks (ie Austrian, Danish, Dutch and Norwegian banks) and euro area countries (ie Austria and the Netherlands), respectively. The two graphs at the bottom show jumps in CT1 in the first quarter of 2008, as Dutch banks (with higher average capital ratios) are reported from that time onwards.

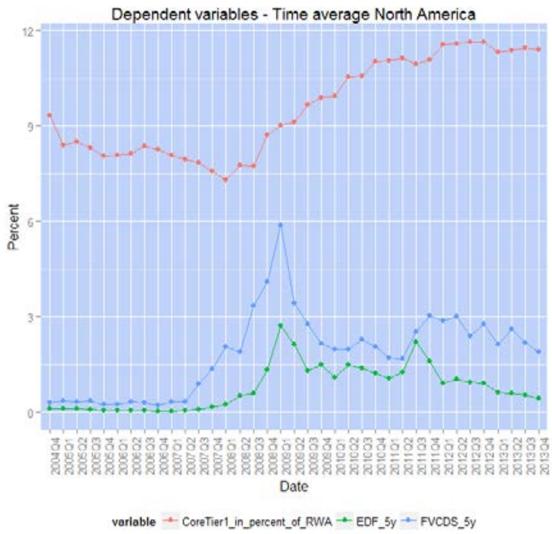
Cross-section averages of CT1 ratios, EDFs and CDS

Graph C.2

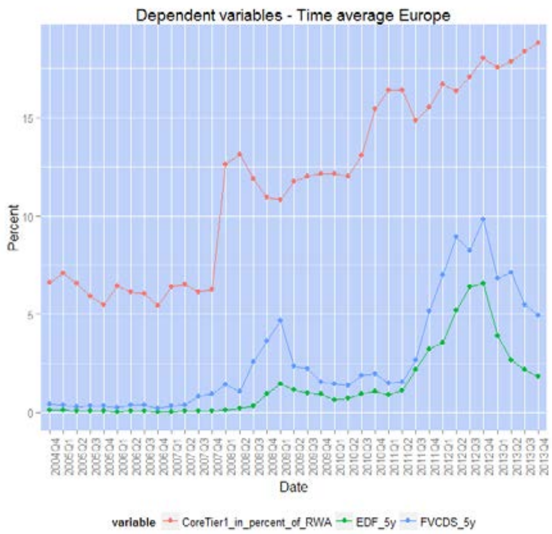
Full sample



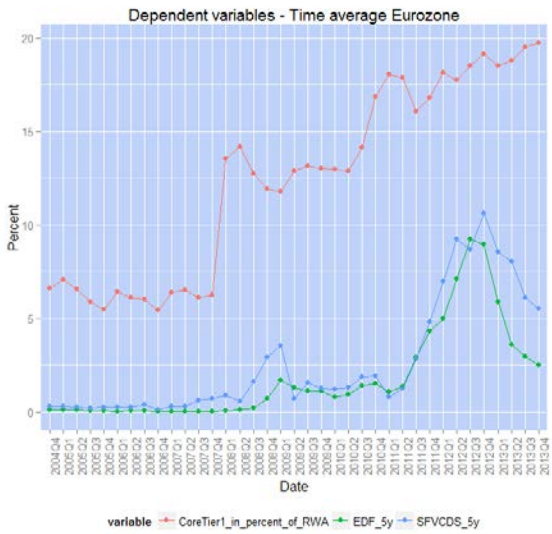
North America



Europe



Euro area



Sources: Various central banks and regulatory agencies, Moody's KMV.

Table C.2 reports the summary statistics for bank solvency, funding costs, bank-specific variables, country-specific variables and global variables. Table C.3 shows the correlation matrix structure of the variables used in the specification.

Summary statistics of the dependent and independent variables

Table C.2

Variable name	Mean	Min	First quartile	Median	Third quartile	Max	NAs	Variance
CapitalIncreaseD	0.04	0	0	0	0	1	423	0.04
CDS_gov	0.39	0.01	0.22	0.35	0.48	1.85	483	0.09
CT1	10.5	-13.7	7.89	9.42	11.55	111.2	366	95.29
crisesD	0.57	0	0	1	1	1	0	0.25
EDF_5y	0.86	0.01	0.08	0.3	0.94	21.43	373	2.57
FVCDS_5y	1.97	0.01	0.45	1.31	2.49	17.44	381	4.94
LIBOR_OIS_aq	0.32	0.06	0.09	0.16	0.4	2.1	0	0.15
LiRisk	3.49	0	0.28	0.71	1.79	586.5	433	753.8
Loan_growth	0.97	-7.68	-0.08	1.29	2.23	8.15	1	3.72
LoanLossProvisions_ in_total_Assets	0.13	-0.2	0.02	0.06	0.15	1.97	183	0.04
Netincome_in_total_ Assets	0.13	-4.7	0.06	0.17	0.26	2.08	160	0.12
OIS_aq	1.8	0.08	0.15	0.22	3.71	5.35	0	4.18
S_P_rating_scale	5.69	2	5	5	7	11	484	3.29
signDCT12	-0.1	-525.3	-0.03	0	0.14	757.8	423	792.44
signDFVCDS_5y2	0.14	-73.27	-0.04	0	0.09	132	419	34.57
VIX	20.45	11.03	13.6	18.32	24.33	58.32	0	90.78

Source: Various central banks and regulatory agencies.

Cross-correlation matrix of the dependent and independent variables in Section 3.2

Table C.3

	CapitalIncreaseD	CDS_gov	CT1	crisesD	EDF_5y	FVCDS_5y	LIBOR_OIS_aq	LiRisk	Loan_growth	LLPRatio	NIRatio	OIS_aq	S&P Rating	signDCT1^2	signDFVCDS_5y^2	VIX
CapitalIncreaseD	1	-0.00418	-0.05009	-0.00183	0.05344	0.06591	0.21726	0.08012	-0.03062	0.11373	-0.10017	0.02132	-0.02527	0.03504	0.02975	0.18078
CDS_gov	-0.00418	1	0.10066	0.52945	0.40585	0.38901	0.02189	-0.08620	-0.30603	0.05423	-0.00744	-0.50025	0.12189	0.03974	0.03086	0.20584
CT1	-0.05009	0.10066	1	0.19583	0.09060	0.11533	-0.03313	-0.01525	-0.06287	-0.04380	-0.01646	-0.19448	-0.06148	0.13175	-0.04321	-0.00066
crisesD	-0.00183	0.52945	0.19583	1	0.39915	0.47626	0.10752	-0.10177	-0.51889	0.18684	-0.17033	-0.91491	0.25566	0.04191	-0.04540	0.40036
EDF_5y	0.05344	0.40585	0.09060	0.39915	1	0.85804	0.11802	-0.04558	-0.37014	0.29535	-0.21277	-0.38321	0.28459	0.03074	0.18882	0.25967
FVCDS_5y	0.06591	0.38901	0.11533	0.47626	0.85804	1	0.33219	-0.05989	-0.45123	0.34554	-0.32038	-0.49283	0.27902	0.04109	0.24144	0.40282
LIBOR_OIS_aq	0.21726	0.02189	-0.03313	0.10752	0.11802	0.33219	1	-0.03165	-0.24437	0.28560	-0.29208	-0.17017	-0.09194	-0.01518	0.10665	0.85481
LiRisk	0.08012	-0.08620	-0.01525	-0.10177	-0.04558	-0.0599	-0.03165	1	0.06433	-0.04939	-0.03107	0.08242	-0.11630	-0.00523	-0.00103	-0.05206
Loan_growth	-0.03062	-0.30603	-0.06287	-0.51889	-0.3701	-0.45123	-0.24437	0.06433	1	-0.30782	0.20532	0.48733	-0.11235	0.00833	-0.07796	-0.43362
LLPRatio	0.11373	0.05423	-0.04380	0.18684	0.29535	0.34554	0.28560	-0.04939	-0.30782	1	-0.41623	-0.20186	0.25740	0.00629	0.02255	0.36222
NIRatio	-0.10017	-0.00744	-0.01646	-0.17033	-0.21277	-0.32038	-0.29208	-0.03107	0.20532	-0.41623	1	0.18743	-0.04071	-0.00524	-0.24073	-0.31960
OIS_aq	0.02132	-0.50025	-0.19448	-0.91491	-0.38321	-0.49283	-0.17017	0.08242	0.48733	-0.20186	0.18743	1	-0.23921	-0.02625	0.01659	-0.39846
S&P Rating	-0.02527	0.12189	-0.06148	0.25566	0.28459	0.27902	-0.09194	-0.11630	-0.11235	0.25740	-0.04071	-0.23921	1	-0.01126	0.00132	-0.03295
signDCT1^2	0.03504	0.03974	0.13176	0.04191	0.03074	0.04109	-0.01518	-0.00523	0.00833	0.00629	-0.00524	-0.02625	-0.01126	1	0.01957	-0.00563
signDFVCDS_5y^2	0.02975	0.03086	-0.04321	-0.0454	0.18882	0.24144	0.10665	-0.00103	-0.07796	0.02255	-0.24072	0.01659	0.00132	0.01957	1	0.08337
VIX	0.18078	0.20585	-0.00066	0.40036	0.25967	0.40283	0.85481	-0.05206	-0.43362	0.36222	-0.31960	-0.3985	-0.03295	-0.00564	0.08337	1

Source: Various central banks and regulatory agencies.