

# Bank of England

## Macroprudential stress-test models: a survey

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## Macprudential stress-test models: a survey

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### Abstract

We survey the rapidly developing literature on macroprudential stress-testing models. In scope are models of contagion between banks, models of contagion within the wider financial system including non-bank financial institutions such as investment funds, and models that emphasise the two-way interaction between the financial sector and the real economy. Our aim is twofold: first, to provide a reference guide of the state of the art for those developing such models; second, to distil insights from this endeavour for policymakers using these models. In our view, the modelling frontier faces three main challenges: (a) our understanding of the potential for amplification in sectors of the non-bank financial system during periods of stress, (b) multi-sectoral models of the non-bank financial system to analyse the behaviour of the overall demand and supply of liquidity under stress and (c) stress-testing models that incorporate comprehensive two-way interactions between the financial system and the real economy. Emerging lessons for policymakers are that, for a given-sized shock hitting the system, its eventual impact will depend on (a) the size of financial institutions' capital and liquidity buffers, (b) the liquidation strategies financial institutions adopt when they need to raise cash and (c) the topology of the financial network.

**Key words:** Stress testing, system-wide models, contagion, systemic risk, market-based finance, real-financial linkages, sectoral interlinkages, macroprudential policy.

**JEL classification:** G21, G22, G23, G32.

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*“Perhaps at some future date, as financial institutions and risk management systems evolve, aggregate stress tests will be found to be a way to tap into this new data source that would provide forward-looking information about aggregate risk exposures that would be of use to financial firms, central banks, and other financial regulators.”*

Committee on the Global Financial System, April 2000.

## 1 Introduction

The development of frameworks to conduct systematic stress tests of the banking system has been one of the most important innovations in financial regulation in the post-Global Financial Crisis era. These frameworks have informed the calibration of bank capital requirements in many jurisdictions; they have also provided regulators with valuable forward-looking information on the resilience of their banking systems to shocks not previously experienced, including the impact of a disorderly Brexit and the Covid-19 pandemic.

Alongside this, there has been significant research effort in recent years to expand our understanding of how financial systems behave under stress via the development of macroprudential stress testing models. While the typical supervisory stress test centers around an assessment of the direct, first-round impact of a given stress scenario on individual banks’ profitability and capital using a combination of bank-reported estimates and desktop analysis by the regulator, the research effort by contrast has focused on modelling feedback loops within the financial system that can amplify the impact of any external shock. This is a complementary effort, which over time it is hoped will provide regulators with richer tools for identifying vulnerabilities and evaluating policies designed to mitigate systemic risk.

In this paper, we survey the rapidly developing literature on macroprudential stress testing models. Our aim is two-fold: first, to provide a reference guide of the state-of-the-art for those developing such models; second, to distil insights from this endeavour for policymakers that may inform supervisory stress tests. Relative to other related surveys (see [Aymanns et al. \(2018\)](#), [Anderson et al. \(2018\)](#) and [Greenlaw et al. \(2012\)](#)), our main contribution is to take stock of progress in developing models that extend beyond the banking system to capture certain sectors of the broader financial system. In this sense our survey answers directly to recent calls to better understand the non-bank financial system, the financial system as a whole and real-financial linkages ([Cunliffe, 2020](#); [Giese and Haldane, 2020](#)).

For the purposes of this survey, we define a macroprudential stress testing model as one that permits an examination of the resilience of the financial system – or components of it – under stress, taking into account plausible behavioural responses of institutions within the system and the knock-on consequences of those actions for others institutions in the system. Feedback and amplification channels are therefore front and center. The scope of the survey includes models of contagion between banks, models of contagion within the wider financial system including non-bank financial institutions such as investment funds, and models that emphasise the two-way interaction between the financial sector and the real economy. We focus to the extent possible on quantitative models grounded in granular balance sheet data that allow users to examine the magnitude of different channels. That said, the state of the literature is such that much of the work available is cast in stylised, conceptual models and sections of the survey review insights from such models.

Overall, the literature we survey is at different stages of maturity depending on the area of the financial system studied. The literature on contagion dynamics in the banking system is relatively well established. This is particularly so for models focused on solvency contagion operating via interbank exposures and models focused on the interplay between asset fire sales and leverage requirements. In contrast, the literature on contagion channels operating via funding liquidity, including liquidity hoarding effects and dynamics operating via collateralised funding markets, remains in its infancy. A recent strand of the macroprudential stress testing literature attempts to model feedback and amplification channels in the broader financial system, with a particular emphasis on the potential for an amplification loop operating via fire sales and redemptions in the investment fund sector. Despite this recent attention, the potential for contagion in the non-bank financial sector remains less well understood. Finally, while there is a long-established literature examining the implications of embedding financial frictions and crude banking systems in macroeconomic dynamic general equilibrium models, very few papers to date have attempted to incorporate such real-financial sector linkages in a macroprudential stress testing setting.

Given the state of the literature, it is perhaps too early to expect to find robust, widely agreed upon results. That said, there are some noteworthy findings that are common in many of the papers we survey. First, estimates of solvency contagion losses in the banking system tend to be small when models are calibrated to current balance sheets and the current configuration of interbank exposures. Intuitively, this reflects the post-Global Financial Crisis build up in equity capital in the banking system and the reduction in the scale of interbank exposures over the same period. Another common finding, albeit an implicit one, is the importance

of usable buffers of capital and liquidity for mitigating the scale of contagion losses. For instance, there is a large dispersion in the magnitude of loss estimates in the models of fire sales we survey. This dispersion can be traced to differential assumptions about capital buffer usability and price impact estimation, with the largest loss estimates being in models that assume banks have fixed leverage ratio targets with no buffer. Third, an emerging results from the literature on fund stress testing is that the severity of the outcomes depend on assumptions about the liquidation strategy of funds after a redemption shock.

Section 2 provides an overview of the different contagion channels that can operate in the financial system - including banks and non-banks - and between the financial system and the real economy. Having a classification of the channels upfront will provide an overarching structure to the survey and help the reader navigate the following sections.

Section 3 reviews the modelling of contagion channels within the banking sector. We do not aim to provide a complete overview of the literature in this area, and refer readers to surveys by (Glasserman and Young, 2016; Hüser, 2015) for such detail. Rather our aim is to fix ideas about how particular feedback and amplification mechanisms operate in a relatively well understood setting.

Section 4 begins with a brief overview of the main types of non-bank financial institutions (NBFI), setting out the roles they play and the traditional structure of their balance sheets. We then examine which of the contagion channels described earlier apply to these entities; we review the nascent literature that has attempted to model these contagion channels, and we point the reader to accounts of historical examples of systemic stress in this sector. Following this, we zoom in on recent advances in models of fund and central clearing counterparty (CCP) stress testing. And we finish the section by covering the handful of pioneering models of system-wide stress testing, models that include multiple sectors and their interactions.

Section 5 covers models of real-financial linkages. This section takes stock of models to assess contagion due to real-financial linkages. While the linkages between the real economy and the financial sector have been the subject of a great deal of study within the macroeconomics literature,<sup>1</sup> very few models attempt to incorporate these linkages into macro-prudential stress-testing models. With that in mind, that section will first provide a brief and selective overview of the (very broad) literature covering the relevant linkages between the financial sector and real economy. Then it will discuss models which incorporate these linkages, organizing the literature into the different modelling approaches used and discussing their relative merits.

Section 6 discusses indicators that can capture and summarise the sources of risk for banks and other financial institutions. Overall, this section aims to shed light upon the different types of outputs that a macroprudential stress testing methodology may deliver.

In the concluding section of the paper, we draw out some take-away lessons from this survey. We first discuss lessons for financial stability policymakers, where the emphasis is on emerging insights from this literature that can inform the design of supervisory stress tests. We then discuss lessons for researchers involved in developing macroprudential stress testing models, where our emphasis is prioritising addressing gaps in this literature that impede the utility of these models for informing policy.

## 2 A brief primer on contagion channels

In this section we provide an overview of the different contagion channels that can operate in the financial system - including banks and non-banks - and between the financial system and the real economy. Having a classification of the channels upfront will provide an overarching structure to the survey and help the reader navigate the following sections.

The academic literature has identified two key types of links along which contagion can propagate: direct and indirect links. Examples for those direct links are loan exposures in the interbank market, leveraged investment funds debt-like liabilities held by other financial institutions and banks' loans to non-financial firms. Indirect links include for example overlapping portfolios or correlated assets.

Direct links connect borrowers and lenders, and hence the trigger for contagion can be caused by the distress of either the borrower or the lender. If the borrower is in distress (for example because it defaults), this implies it is unable to repay its liabilities to its counterparties. Since these liabilities are other agents' assets, these agents may now get in trouble, thereby affecting their counterparties. This is how a default cascade starts. This contagion channel works via counterparty risk, where the borrower cannot pay back the lender. It is therefore called in this survey *direct contagion via the solvency channel*. If the lender is in distress (for example because of a liquidity shock), it may decide to increase their cost of lending or pull their funding altogether. This in turn will cause a liquidity shock for the borrower which may also use similar defensive actions with his own counterparties. This contagion channel works via funding risk and is therefore called in this survey *direct contagion via the funding-liquidity channel*.

Indirect links connect agents holding the same or similar assets via changes in asset prices. This contagion channel works via market-liquidity risk and is therefore called in this survey *indirect contagion via the market-*

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<sup>1</sup>For a recent survey, see Claessens and Kose (2018).

*liquidity channel*. This contagion channel can operate over different timescales. On long timescales, across years or decades, it concerns agents - such as insurance companies - with long investment horizons who can adjust to long term trends in asset prices. On a shorter timescale, such as days, weeks and months, contagion can be caused by fast sales of assets at distressed prices, often called *fire sales*. Asset sales can be driven by investors' redemptions, such as in the case of investment funds, or violation of capital adequacy constraints, such as in the case of banks, for example.

In the following sections 3, 4 and 5 we provide more details on these channels for each 'system' under consideration, beginning with the 'narrowest' system i.e., banking system, then the wider financial sector including non-banks, and finally turning to interactions both to and from the real economy. When discussing contagion in the banking sector and beyond banks, in sections 3 and 4 respectively, we reserve a separate discussion for *contagion channels involving collateral*. This is because the use of collateral for trading and lending, while mitigating counterparty risk, can generate both direct (via the funding-liquidity channel) and indirect (via fire sales) contagion channels.

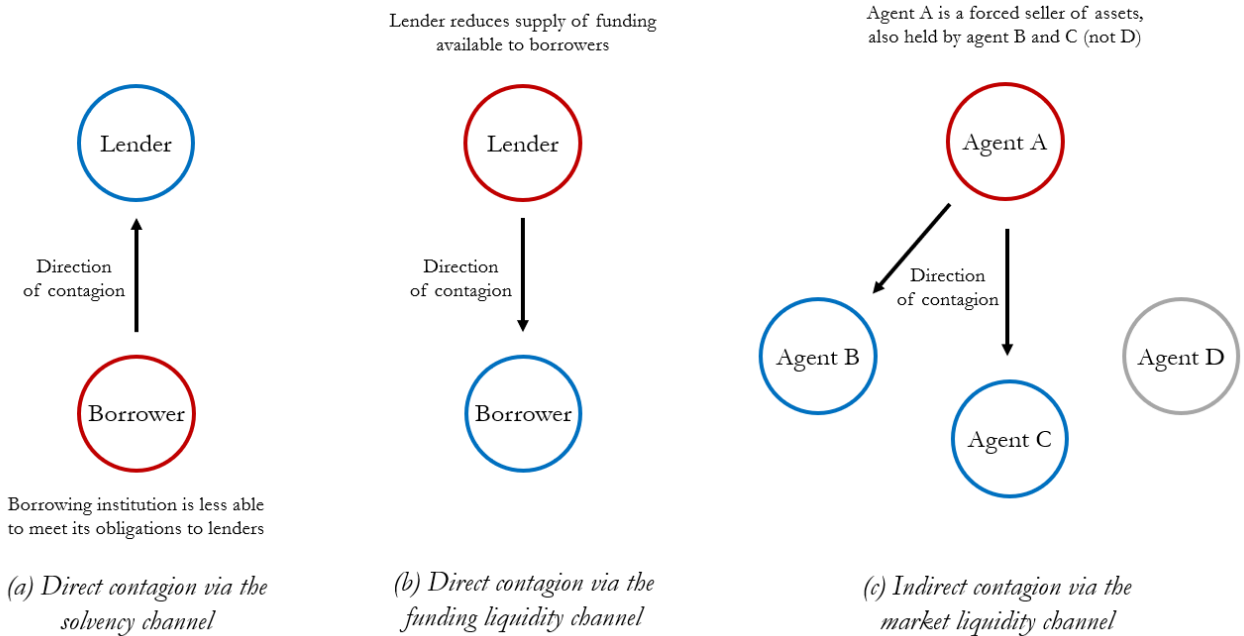


Figure 1: Contagion channels.

### 3 Contagion in the banking sector

In this section, we first review the state of the art in models that capture contagion channels for the banking sector in isolation. We then review papers that attempt to model different contagion channels' interaction. Our focus is on models that can be calibrated with granular data from banks' regulatory returns, and hence be used to provide quantitative analysis to inform financial stability policy. One alternative approach to modelling contagion in banking systems is to use reconstructed interbank network data; another is to use financial market data to infer the strength of bilateral network connections between banks, We refer the reader to [Gandy and Veraart \(2017\)](#) for a review of the literature on reconstructed interbank networks, and to [Diebold and Yilmaz \(2014\)](#), [Engle et al. \(2015\)](#) and [Tobias and Brunnermeier \(2016\)](#) for a review of the literature on using financial market information to estimate networks.

There has been a notable increase in the availability of granular banking sector data since the Global Financial Crisis of 2008-2009, and this has enabled modellers to make significant progress in quantifying the importance of these contagion channels. In this survey, we focus on reviewing such progress in the academic literature on contagion models in the banking sector. A review of the macro-prudential stress testing frameworks of regulatory and monetary authorities is out of the scope. We refer the readers to [Anderson et al. \(2018\)](#).

Overall, it is important to be mindful of the fact that these models are highly sensitive to different modelling assumptions and that some parameters (e.g. the market liquidity of specific asset classes) are hard to calibrate. Hence, point estimates from these models should be interpreted with caution. A more profitable approach for using such models in a policy setting is the framework they provide for understanding what might happen. Are there reasonable calibrations of key parameters where severe contagion occurs? What would we need to believe

about shocks, balance sheet positions or market liquidity for this to be the case? Which policy interventions are most successful at steering the system away from such dire outcomes?

### 3.1 Direct contagion via the solvency channel

The seminal paper that introduced a modelling framework for analysing direct contagion via the solvency channel in the interbank market is Eisenberg and Noe (2001). The paper considered a network of firms with interfirm debt claims and analysed the vector of clearing payments that occur upon the default of one firm. In this model, when a bank is not able to repay its debt in full it defaults. This in turn can trigger a cascade of further defaults, when the creditors that fail to receive some payments from their counterparties are not able to pay their own creditors. The authors show that a clearing payment vector always exists and, under mild conditions, is unique. This model has been highly influential and has set the basis for an extensive literature applying its clearing mechanisms to the study of different aspects of an interconnected financial system.

The Eisenberg and Noe (2001) model is, however, based on some strong simplifying assumptions. In particular, it assumes that when a bank defaults, the full face value of its remaining assets is distributed to its creditors pro-rata. In reality, bank defaults generate significant legal costs and there are substantial delays in paying back creditors.<sup>2</sup> Furthermore, claims on a bank's assets have different seniority in practice. Elsinger et al. (2009) has considered the implications of accounting for cross holdings of equity as well as a detailed seniority structure of debt in the interbank network. In this model the value of equity and debt of the banks are determined endogenously. While in Eisenberg and Noe (2001) equity values are convex and debt values are concave in the exogenous income, this is not the case anymore.

Rogers and Veraart (2013) have extended this framework to allow for non-zero bankruptcy costs. In their model when a bank defaults it does not realize the full value of its assets but only a fraction. Introducing default costs generate incentives for rescue consortia, that is there is a benefit for solvent banks to rescue insolvent ones. However, the authors note that given the practical challenges in implementing a rescue consortium, a lender of last resort would be required as an appropriate coordination mechanism in this framework. At the same time, as also discussed in Elliott et al. (2014) which accounts for discontinuous losses when banks' value falls below the failure threshold, non-zero bankruptcy costs also create incentives for a bank to increase its failure costs and make its failure more likely, in order to increase its negotiating power.

Elliott et al. (2014) adopts the model to study how cascades of failures depend on the *network structure*, topic highly debated in the literature.<sup>3</sup> In particular, they are interested in studying how cascades of failures depend on the network integration (i.e. dependence on counterparties in terms of *level* of exposures) and diversification (i.e. *the number* of firms' cross-held). Increasing integration leads to increased exposures, hence can increase the likelihood of a cascade once an initial failure occurs. However, it can also decrease the likelihood of observing a first failure. Diversification increases interdependencies in the network, allowing contagion to cascade, but it also makes firms less sensitive to other firms' failures.<sup>4</sup> As reported in Hüser (2015), while there is agreement on the existence of this trade-off, the literature has not provided a conclusive answer on the ultimate effect of connectivity and its desirable level, answer which depends on other factors as well. For example, an additional factor to consider is potential 'errors in the structure of the contract network' as defined by Battiston et al. (2016), that is information regarding how many contracts a bank has and with which counterparties may be incorrect. Higher diversification can result in market participants and regulators knowing less precisely the probability of systemic default. Another factor to consider is the size of the initial shock. Acemoglu et al. (2015) finds that a more diversified network of interbank liabilities leads to a less fragile financial system, in the presence of relatively small shocks. However, when shocks becomes larger more interconnected network structures can facilitate contagion and create a more fragile system. This is because under large shocks excess liquidity of the banking system can become insufficient to absorb losses, and in a less diversified network losses are shared with the creditors of the distressed banks only, protecting the rest of the banks. This finding is similar to the one by Georg (2013), when banks can optimize their balance sheet and as a result the interbank network structure, and is consistent with the 'robust-yet-fragile' property as explained by Haldane (2009). Glasserman and Young (2015) adopts a full-fledged distribution of shocks and analyze the probability of default cascades that are attributable to network connections. They show that, while solvency contagion losses have only limited

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<sup>2</sup>As an example of such costs, Denison et al. (2019) estimate the total value destruction associated with Lehman Brothers' Chapter 11 Bankruptcy is likely to be between 46 billion and 63 billion, or 15 – 21% of Lehman's pre-bankruptcy consolidated assets. This estimate includes both direct costs paid to third parties (e.g., legal and accounting professionals) and indirect opportunity costs associated with factors such as the disruption to financial services provided by Lehman and liquidity cost of having assets trapped in lengthy bankruptcy proceedings.

<sup>3</sup>Pioneering theoretical papers assessing this question, Allen and Gale (2000) and Freixas et al. (2000), had found that highly connected interbank network enhances the resilience of the system to the insolvency of an individual bank. We refer to Hüser (2015) for a complete review of studies that investigate the interaction between contagion risk and network structure for interbank networks.

<sup>4</sup>In particular, after reaching a particular threshold, further increase in diversification reduce widespread contagion likelihood. Given these trade-offs, they conclude that a system is most susceptible to widespread contagion when integration is intermediate and firms are partly diversified.

impact, the network is more vulnerable to contagion when the shock originate on a bank which is large, highly leveraged and highly connected. Policy makers have also reflected on the relationship between network structure and systemic risk, in particular in the aftermath of the global financial crisis (Haldane (2009), Yellen (2013)), and have introduced policy measures targeted to reducing these vulnerabilities, e.g. the Basel Committee on Banking Supervision leverage ratio requirements and limits on large exposures.<sup>5</sup>

Another important stream of recent research on solvency contagion has focused on modelling *pre-default* contagion. The Eisenberg and Noe (2001) model makes the strong and unrealistic assumption that contagion propagates from one firm to another only after an outright bank default occurs. This is equivalent to assuming there is no ex-ante uncertainty about the ability of a bank to repay its debt and therefore whether or not it will default. As a consequence, losses cannot crystallise before maturity. In practice, outside creditors do not have such information. As a result, they will take into account any deterioration in the bank's creditworthiness when valuing their exposures to the bank in question. This, in turn, can impact the total value of creditors' assets, and hence their own probability of default. As a consequence, distress can propagate pre-default. Battiston et al. (2012), Bardoscia et al. (2016), Fink et al. (2016), Barucca et al. (2020) and Veraart (2020) present extensions of Eisenberg and Noe (2001) to account for this case. In particular, Battiston et al. (2012) develops a measure of systemic importance of a bank, called DebtRank, which accounts for the fraction of economic value in the network that is potentially affected by the distress of the bank. Even when none of the banks in the network defaults initially, initial shocks always generate an impact larger than the shocks themselves, even before the peak of the crisis. In this model the magnitude of contagious losses is determined by the probability of default, which is a linear function of the relative equity loss, extended to be non-linear in Bardoscia et al. (2016). Other papers have taken different approaches: in Fink et al. (2016) counterparty risk valuations are based on heuristic rules, in Barucca et al. (2020) they are grounded in valuation functions derived from a clearing mechanism, in Veraart (2020) they are assumed to take different functional forms. The advantage of this latter approach is that it allows for a wide range of possible functional shapes relying on a small set of parameters.

The paper shows that allowing for pre-default contagion will always lead to worst or at best equal outcomes of the stress test compared to only allowing for contagion at default. Hence, these results stress the importance of accounting for pre-default contagion for policymakers, as only looking at post-default contagion - which is still quite common in regulatory stress testing models - could lead to under-estimation of losses from this channel.

In addition to enriching the modelling assumptions of Eisenberg and Noe (2001), the literature has benefitted in recent years from having access to more detailed regulatory data on banks' direct exposures. Prior to the Global Financial Crisis, such data were scarce and incomplete, and analyses of systemic risk in interbank networks studies relied on estimated or partial data on banks' bilateral exposures – examples of such analyses include Wells (2004) for the UK, Furfine (2003) for the US and Upper and Worms (2004) for Germany.<sup>6</sup> These studies reached divergent conclusions: some found that the risk of contagion was low (Furfine (2003)); others found it had the potential to affect a large part of the banking system (Upper and Worms (2004)). However, as acknowledged by Wells (2004), 'data constraints mean that drawing definitive conclusions is difficult'. We refer to Upper (2011) for a thorough review of pre-crisis research using simulation methods to assess the danger of contagion in interbank markets, including a discussion of potential sources of bias. In the period since the 2008 crisis, the availability of regulatory data on interbank exposures has expanded greatly, permitting a more accurate analysis of the risk of solvency contagion in such networks.

We summarise the findings of papers that use such data for modelling solvency contagion in interbank networks in Table 1. Despite their focus on different banking systems and the different modelling assumptions made, these studies reach similar conclusions. In particular, they find that solvency contagion risk in the interbank market has fallen significantly since the Global Financial Crisis era. For example, Bardoscia et al. (2019) apply the framework of Barucca et al. (2020) to study solvency contagion risk in the UK banking system.

They find that contagion risk has fallen as a result of both the increase in banks' capital ratios and the decrease in the scale of interbank exposures. This is in line with the findings of Nier et al. (2007), which find that the better capitalised banks are, the more resilient is the banking system against contagious defaults and this effect is non-linear. Abduraimova and Nahai-Williamson (2021) confirm this finding for the UK interbank system building on the model of Bardoscia et al. (2019). Similar findings have been found for the Brazilian interbank market in Souza et al. (2015), and for the Euro Area when considering direct contagion risk related to the bail-in of other banks holding securities issued by banks entering resolution (Hüser et al. (2018)).

When looking at the impact of different parameters we note that the recovery rate at default plays an important role. Bardoscia et al. (2019) shows that the recovery rate has significant implications in terms of the size of contagion losses. When the recovery value is zero losses due to contagion can be as large as losses due to

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<sup>5</sup>See [https://www.bis.org/fsi/fsisummaries/b3\\_lrf.htm](https://www.bis.org/fsi/fsisummaries/b3_lrf.htm) and [https://www.bis.org/basel\\_framework/standard/LEX.htm](https://www.bis.org/basel_framework/standard/LEX.htm) for more details.

<sup>6</sup>There were some exceptions: Banca d'Italia and Banco Central do Brasil collected detailed data on banks' bilateral exposures. Using Italian bank data, Mistrulli (2011) shows that contagion based on actual exposure patterns tends to exceed contagion based on hypothetical exposure patterns. We also note that BIS International Consolidated Banking Statistics database can be used for network analysis for cross-border financial surveillance, see Espinosa-Vega and Solé (2011).



the exogenous shock. For higher recovery rates losses are smaller. For example in their model calibrated with 2008 data, aggregate contagion losses reach 140 £billions under zero recovery rate, for an initial 70% equity shock, while under a recovery rate of 0.8 everything else equal losses are more than five times smaller.

<i>Models</i>	Hüser et al. (2018)	Fink et al. (2016)	Bardoscia et al. (2019)	Souza et al. (2015)
<b>Initial shock</b>	Idiosyncratic shock to a bank's assets (1% – 12% of total assets)	Shock to real estate sector (15 pp change in loss given mortgage default)	Equity shock (30%, 50%, 70%)	Fictitious initial default of a single institution
<b>Solvency contagion trigger</b>	Bail-in (write-down and recapitalization)	Increase in probability of default	Increase in probability of default	Default
<b>Recovery rate</b>	Dependent on seniority of exposure (the write-down can be complete or partial)	0.55	0, 0.4, 0.6, 0.8	0
<b>Banking system</b>	EU 26 largest euro area banking groups  (ESCB and ECB datasets)	Germany 1710 banks  (Deutsche Bundesbank's credit register)	UK 7 major banks  (Bank of England regulatory data)	Brazil 265 banks, credit unions or cooperatives, brokers/dealers (Brazilian supervisory exposure data)
<b>Time period</b>	2015	2013	2008-2016	2008 and 2011, 2012
<b>Contagion Losses</b>	[0, 0.2%] decrease in other banks' CET1 ratio	0.5% of total CET1	~ 0 £bn in 2016, [20, 140] £bn in 2008	24% of total interbank assets in 2012, 47% of total interbank assets in 2008

Table 1: Models of direct contagion via the solvency channel models with empirical applications using detailed information on interbank exposures.

### 3.2 Direct contagion via the funding-liquidity channel

Another important direct contagion channel is from lenders to borrowers, referred here to as direct contagion via the funding-liquidity channel. Papers written either before or in the immediate aftermath of the Global Financial Crisis tended to focus on unsecured funding markets, motivated by the freeze in interbank markets that became a hallmark of that crisis. More recently, attention has shifted to secured funding markets and the role of collateral. This reflects the significant growth in collateralised funding markets in the past decade. Furthermore, repo markets have displayed signs of fragility during recent stress episodes, such as that which occurred in the US repo market in September 2019 (Anbil et al. (2021)) and the COVID-19 dash for cash episode in March 2020 (Hüser et al. (2021)). Here we focus on direct contagion channels via funding-liquidity channels, including in collateralized funding markets, but reserve a separate broader discussion on channels - including indirect contagion - involving collateral (see Section 3.4).

The literature has identified several triggers that can cause liquidity to dry up in funding markets. The first potential cause of such an occurrence is *solvency or liquidity problems* at borrowing institutions. For example, firms suffering increased solvency risk are likely to experience increases in the cost and reductions in the availability of unsecured funding. This creates the possibility of a feedback loop whereby deteriorating bank solvency increases counterparty risk, leading to increases in the cost of funding, eroding bank solvency further. Dent et al. (2017) study the empirical importance of this channel for UK banks.

They find that negative shocks to a bank's market leverage ratio (i.e., the market value of equity over the book value of assets) are associated with increases in its marginal cost of wholesale funding. Similarly, Schmitz et al. (2019) find a two-way relationship between regulatory capital ratios and funding costs for EU banks. This channel can also operate via changes in market participants' perceptions of bank solvency, leading to the prospect of information contagion among banks that are perceived to be similar (Acharya and Yorulmazer (2008)). Increased funding costs can also adversely affect banks that are already suffering funding shortfalls, as they scramble to find substitute funds.

Another important channel that can cause funding liquidity to dry up in both secured and unsecured markets is precautionary *hoarding* behaviour by liquidity suppliers. Such behaviour could be prompted either by a liquidity shortage (Gai et al. (2011)), a desire to reduce risk exposures (Anand et al. (2012)) or by strategic considerations and the value of retaining dry powder to take advantage of future asset sales at fire sale prices (Diamond and Rajan (2011)). One of the first paper to model contagion effects from liquidity hoarding using a network approach is Gai et al. (2011). This study analyses the potential for liquidity hoarding in unsecured interbank markets to propagate through a stylised financial network. In this model if a bank faces a liquidity

shortage, triggered by shocks on haircuts in the repo market (which then requires the bank to post more collateral to obtain the same amount of repo funding) or loss of interbank funding, it hoards liquidity. That is, the bank withdraws unsecured interbank assets from counterparties it was lending to, thus further propagating liquidity shortages in the network.

The model is used to simulate contagion dynamics and study tipping points under different model parameters and network structures. They show that systemic liquidity contagion is highly non-linear in the haircut shock size and network connectivity, with aggregate haircut shocks combined with high connectivity producing the worst outcome. They also investigate the impact of concentration and complexity. For a broad range of connectivity, higher network concentration makes it more susceptible to a systemic liquidity crisis. Complexity, defined as increased interbank liabilities both in the secured and unsecured market, also increases the likelihood of contagion. Finally, the model provides important policy implications: increasing liquid asset holdings reduces the system susceptibility to liquidity crises, even more so when liquidity requirements are targeted to banks with higher-than-average interbank assets, i.e. more instrumental in spreading contagion. Interestingly the authors also suggest, given the cyclical tendencies of haircuts, to implement time-varying liquidity requirements. In the aftermath of the Global Financial Crisis regulators have strengthened banks' liquidity regulation, for example by introducing the Basel III Liquidity Coverage ratio (LCR). The LCR ensures that banks hold sufficient liquid assets to cover potential outflows in stress. Even though the LCR is not explicitly time-varying, banks can reduce their LCR in a stress. During the dash-for-cash in the early months of the COVID-19 crisis, regulators have indeed used this flexibility.

Anand et al. (2012) also studies systemic risk due to funding withdrawals accounting for network dynamics and strategic interactions. In this model banks withdraw funding to minimize losses when they receive bad news about their creditors' viability. Crucial features of the model are the rate at which bad news about the creditworthiness of a bank arrives and the maturity structure of debt contracts. In the case that interbank loans have lengthy maturities in comparison to the rate at which bad news arrives, once a crisis tips the system into a 'bad equilibrium' where the credit network is sparse because banks are more skittish and prone to prematurely foreclosing, the restoration of credit relations requires considerable effort.

Cont et al. (2020) presents a stress testing framework for capturing both an increase in funding outflows and cost of funding due to a deterioration of solvency. In the model, banks raise funding in both the unsecured market and in the repo market, as well as by selling assets. A deterioration in solvency positions can lead credit sensitive funding outflows and an increase in funding costs. They show that the amplification effect is non-linear. For small shock sizes, banks can obtain new funding for a relatively low price. When a financial institution defaults due to illiquidity, the cost of new funding is at its maximum. Further, the model allows for liquidity shocks to feedback into the bank solvency position, as an increase in funding costs as well as losses from asset sales deteriorate the bank's equity. The model represent an important contribution to the literature showing how to integrate solvency and liquidity stress testing. However, the model only looks at one bank therefore does not explicitly account for contagion effects. Future research could build upon it allowing for several banks.

### 3.3 Indirect contagion via the market-liquidity channel

Banks that suffer large losses may be forced to reduce risk by selling assets at distressed or *fire sale* prices. When other banks hold these or similar assets, they will be forced to revalue their holdings at these temporarily depressed valuations, creating the potential for distress to spread through the banking system, triggering further destabilising fire sales. Such dynamics feature prominently in accounts of the Global Financial Crisis (Shleifer and Vishny, 2011). Two factors are important pre-conditions for fire sale contagion to occur. First, there must be mark-to-market accounting, i.e. assets must be valued at current market prices.<sup>7</sup> Second, the market's ability to absorb asset sales must be less than perfect, such that asset disposals depress market prices in the short run. This might occur because natural buyers are constrained and assets are sold to non-specialised investors, for instance. At the same time, it requires that arbitrageurs are constrained from taking advantage of the mispricing (Shleifer and Vishny, 1997). The amplification of losses from this channel is likely to be increasing in the degree of leverage and liquidity mismatch in the banking system and when there are large cross-holdings of similar assets across the system.

In this section, we review papers that provide quantitative frameworks for capturing fire sales risks in banks' stress testing frameworks, while we refer to Shleifer and Vishny (2011) for a broader review of the academic literature on the topic. We document the choices authors have made regarding three main components of a fire sale model: (a) the trigger that causes the initial sale; (b) the choice of what assets are sold, i.e., the liquidation strategy; and (c) the reaction of asset prices to sales. These assumptions, as well as the banking system's initial

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<sup>7</sup>Following the Global Financial Crisis, academics as well as practitioners have been questioning the desirability of mark-to-market accounting in view of its procyclicality. We refer for instance to Allen and Carletti (2008), Plantin et al. (2008) and Lepore et al. (2019).

structure, have important implications on the resulting fire sales losses.<sup>8</sup>

One of the first papers to analyse the potential for fire sales in financial networks was [Cifuentes et al. \(2005\)](#). The authors extended a model with direct balance sheet interlinkages between financial institutions a la [Eisenberg and Noe \(2001\)](#) to allow for price-mediated contagion. In this model, financial institutions face capital adequacy constraints that place a lower bound on the value of their equity relative to assets. When this constraint is violated, they are forced to sell assets to improve their solvency ratio. The equilibrium price at which these sales take place is endogenous, determined by the intersection of a downward-sloping market demand curve and a vertical supply curve. The main contribution of the paper is to show the existence of a joint clearing vector of payments and prices in systems with both interbank liabilities and a single marketable illiquid asset subject to fire sale dynamics.

When simulating this stylised model for a hypothetical banking system, the authors find that the fire sale mechanism can, in some circumstances, trigger a dramatic cascade of further asset disposals and mark-to-market losses. Key parameters determining the scale of contagion are the liquid asset holdings of the system and its interconnectedness (i.e., the average number of counterparties a particular bank has). One noteworthy finding is that the level of systemic risk in the system is a non-monotonic function of interconnectedness, with systemic risk lowest when the number of average counterparties is either very low or very high. Another is the existence of a threshold level of liquid asset holdings beyond which fire sale contagion does not occur. Several papers have extended this framework, including [Amini et al. \(2016\)](#) who showed equilibrium uniqueness under mild assumptions, and [Feinstein \(2017\)](#) who allowed for multiple illiquid assets.

A recent strand of the literature has focused on quantifying the importance of the fire sale mechanism in real-world financial networks using regulatory data on banks' asset positions. The seminal paper here is [Greenwood et al. \(2015\)](#). Motivated by empirical evidence on leverage targeting ([Adrian and Shin, 2010](#)), [Greenwood et al. \(2015\)](#) developed a simple fire sales model where banks sell assets in order to maintain leverage targets. In particular, the authors assume that, when they suffer losses, banks sell assets proportionately to their existing holdings. The price impact of sales is assumed to be linear and proportional to the total amount of asset sales across the banking system. Moreover, the authors assume that all assets have the same market depth. The model is calibrated to match the asset holdings of the the European banking system in 2011. The authors model the impact of a shock that generates a 50% write-off in banks' holdings of Greek, Italian, Irish, Portuguese and Spanish sovereign debt (see [Table 2](#)). They find that the fire sale channel considerably increases the losses generated by this shock: losses of the average bank in the system jump by 302%.

The assumption that banks have fixed leverage targets that they are unwilling to deviate from is a strong one, and several recent papers have explored the implications of relaxing it. [Duarte and Eisenbach \(2013\)](#) model banks as instead having a latent leverage target, which is both time varying and to which the speed of adjustment varies. They apply this framework to study how vulnerability to fire sales cascades has evolved in the US banking system in the years preceding the Global Financial Crisis. They show that the aggregate vulnerability of the system – defined as the percentage of system-wide equity capital at risk due to fire sale spillovers – displays large variation over time. In particular, the measure builds from around 12% in 2001, peaking at 38.3% in 2007.

[Cont and Schaanning \(2017\)](#) propose an alternative non-linear decision rule for bank deleveraging, in which banks begin to sell assets only when their leverage crosses a certain threshold. This threshold could be taken to capture regulatory requirements that the ratio of equity to total assets exceeds a certain minimum; it could also capture the impact of a 'voluntary' or 'market-determined' leverage ratio buffer. These assumptions mean that spillover losses attributable to fire sales will depend on the initial equity position of the system and the scale of shocks it faces. The authors also allow for heterogeneous market depths for illiquid assets. When calibrating the model to the European banking system, the paper finds smaller spillover losses relative to models that adopt constant leverage targeting. In particular, conditional on the same size shocks as used in [Greenwood et al. \(2015\)](#), the loss suffered by the average bank is three times smaller, although remains sizable.

Recent extensions of this framework have focused on refining banks' liquidation strategies. For example, [Braouezec and Wagalath \(2018\)](#) study optimal liquidation strategies in the presence of risk-based capital requirements. [Coen et al. \(2019\)](#) present a framework in which banks face risk-based capital, as well as leverage and liquidity constraints. When a constraint is hit, banks optimise their asset sales, trading off liquidation losses against the impact a given sale will have on the constraint in question. The authors find that while solvency shocks (i.e., losses on exposures) typically trigger only modest fire sale losses, the losses that result from funding liquidity shocks (e.g., outflows from depositors and wholesale funding) can be significant. [Braouezec and Wagalath \(2019\)](#) analyse the strategic dimension of banks' liquidation strategies, when banks face a risk-based

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<sup>8</sup>Most of the papers in this literature take the initial structure of the system, that is banks' initial balance sheet and connections, as given. They then consider the ex-post modelling of asset contagion by fire sales, i.e. banks manage their assets after the shock has occurred. By contrast [Awiszus et al. \(2022\)](#) undertake an ex-ante analysis of banks' balance sheet holdings and develop an explicit characterization of the distribution of banks' holdings that maximizes market efficiency ex-ante accounting for fire sales. They find that portfolio diversification is efficient if asset price shocks are homogeneous and banks are heterogeneous in terms of their systemic significance.

capital ratio and can only sell one type to asset. In this model banks anticipate the negative externality of other banks' liquidations. They find that the Nash equilibrium of the liquidation game they study is characterised by strategic complementarities in selling behaviour. That is a bank has an incentive to liquidate more risky assets when the other banks increase their volume of fire sales.

<i>Models</i>	Greenwood et al. (2015)	Cont and Schaanning (2017)	Duarte and Eisenbach (2013)	Coen et al. (2019)
<b>Sales trigger</b>	Leverage Target	Leverage Threshold	Partial adjustment to target leverage	Solvency and Liquidity constraints
<b>Liquidation rule</b>	Proportional	Proportional	Proportional	Optimal (loss minimizing)
<b>Marketable assets</b>	All assets	Corporate and Sovereign exposures (bonds, equities, derivatives)	Most assets (loans, bonds, equities and other securities)	Corporate and Sovereign exposures (bonds and equities)
<b>Price impact</b>	Homogeneous across all assets (Impact of 10 bn is 10 bp)	Heterogeneous (based on ADV) (Impact of 10 bn ranges from 1.8 to 1355 bp)	Heterogeneous (based on NSFR haircut) (5 – 100%)	Heterogeneous (based on ADV) (Impact of 10 bn ranges from 1 to 720 bp)
<b>Banking system</b>	EU 90 largest banks (EBA data)	EU 51 banks (EBA data)	US 100 largest banks (Federal Reserve Board data )	UK 7 major banks (BoE regulatory data)
<b>Time period</b>	2011	2016	1999 - 2016	2016
<b>Shocks</b>	40.1 (% CET1)  (50% write-off of sovereign debt of all GIIPS)	[0-20] (% CET1)  (EBA scenario and variants)	1% shock all assets	Solvency shock: [25%, 50%] CET1 Liquidity shock: [0%,22%] (outflows % b.s.)
<b>Total fire sale losses (% CET1)</b>	245	[0-50]	22 (average across time)	Losses under solvency shock: [0,10%]; Losses under funding shock: [0,37%]

Table 2: Fire sales contagion models with empirical applications using detailed information on banks' asset positions. ADV stands for average daily volumes. We report the results from Duarte and Eisenbach (2013), rather than the published updated version of the paper, to enhance comparison with the others.

### 3.4 Contagion involving collateral

Counterparty risk can be mitigated by lenders requiring collateral, which provides a buffer against the spread of losses through the system. However, its use creates additional channels via which liquidity distress can propagate. As changes in regulation and industry practices after the Global Financial Crisis led to increased use of collateral in trading and lending, collateral channels gained more importance. In particular, we can distinguish the following channels.

First, changes in collateral values and requirements can act as a trigger of direct contagion. Changes in haircuts in secured funding markets can generate a funding squeeze for borrowing institutions, who must then dip into cash buffers, secure additional funding or sell assets, with knock-on consequences for other intermediaries in the system. Gai et al. (2011), as described previously, models the contagion from banks withdrawing liquidity from each others due to an increase in haircuts on their repo funding. Increases in margin calls on derivative contracts have economically similar effects. Paddrik et al. (2020) simulates margin calls from a credit shock in the US CDS market and study the direct contagion produced by banks defaulting due to the inability to meet their payment obligations from variation margins in full. Such failure leads to payment shortfalls which amplify the initial shock in the network. When calibrating the model to the Fed Comprehensive Capital Analysis and Review (CCAR) shock they find that one firm, which is large and has unbalanced buy and sell positions, is responsible for a significant portion of total systemic losses. Further, they show that CCP members tend to amplify contagion due to their central position in the network. By contrast the CCP, despite being the most central node, contributes little to contagion thanks to its perfectly matched portfolio, stringent initial margin requirements and large guarantee fund. The model can also be used to evaluate the effectiveness of tightening initial margin requirements or increasing firm' liquidity buffers. In their empirical analysis, due to the extremely large initial shock, both measures have only a moderate effect in terms of reducing shortfalls and the percentage of firms in default and come at the cost of posting or holding additional collateral.

Bardoscia et al. (2021) also simulates margin calls, for the European OTC interest rate and FX derivatives, but they are interested in the case where liquidity shortfalls leave firms solvent and result in actions to raise new liquidity, for example in the repo market. When liquid-asset buffers are insufficient to cover the shortfalls, firms

borrow additional liquidity but this results in payment delays which can spread liquidity shortfalls through the network. They call this the domino component of liquidity shortfalls, part of which can be avoided by an external authority coordinating payments. They show that aggregate shortfalls are generally larger when liquid-asset buffers are smaller and when group members operate on a standalone basis and have to exchange variation margins between themselves. Further, they show that a regulator wanting to inject liquidity in the system should target firms with larger bang-for-buck ratio, i.e. the ratio of its contribution to the aggregate shortfalls and its individual shortfall, as such injections would be positively amplified yielding a reduction in the aggregate shortfall that is larger than the injection itself.

Second, collateral held in less liquid assets can create a channel for indirect contagion. For example, in the event an institution defaults, its counterparties would seize and liquidate collateral. Thus on one hand a bank may benefit from the failure of another, if the failure frees collateral. However, collateral sales could depress prices, lowering the value of collateral held by other institutions, who could also need to post additional collateral as a result. Thus spreading losses in the system via fire sales. This channel is accounted by [Ghamami et al. \(2022\)](#) who shows that collateral illiquidity increases defaults and payment shortfalls. Their results add to the debate on the desirability of permitting less liquid collateral in derivatives and repo contracts.

Finally, collateral rehypothecation - i.e. when the lender can re-use the collateral to secure another transaction - creates an additional source of distress propagation by increasing leverage and allowing different institutions to rely on the same set of collateral. Hence, while rehypothecation increases funding liquidity, it can also generate contagion risks. [Luu et al. \(2021\)](#) developed a network model of repo collateral chains to study the contagion channel generated by institutions hoarding collateral when facing a shock, in turn constraining the availability of collateral and its re-use for other institutions. In particular, as banks hoard to minimize liquidity default risk, the hoarding rate of a bank is in equilibrium a function of the hoarding rates and collateral of the banks it is connected to. As a result an increase in hoarding rates at some banks can increase other banks' hoarding rates, even if indirectly connected, depending on the structure of the network. The authors show that core-periphery structures are the most vulnerable to large collateral losses when shocks hit central nodes.<sup>9</sup> However, this type of network can also generate larger collateral volumes relative to other network structures, when hoarding rates are not responsive to other banks' liquidity positions. In this case, when collateral flows are concentrated in the core, a small increase in the network density leads to significant increase in collateral 'velocity' and hence a more liquid market where banks can secure a larger set of secured lending contracts.<sup>10</sup> These results emphasize the trade-off generated by collateral rehypothecation between the creation of liquidity and systemic liquidity risk. This practice, although being widespread, is indeed the subject of debate in policy circles. We refer to [Financial Stability Board \(2017\)](#) for a review of potential financial stability issues in relation to re-hypothecation and discussion of regulatory practices and policy recommendations for addressing residual financial stability risks.

### 3.5 Interaction of direct and indirect contagion

In reality direct and indirect contagion co-exist and interact in the financial system, leading to cross-amplification effects. Below we review papers that explicitly model both channels and study these amplification effects (see [Table 3](#) for an overview).

Early contributions to the literature studying multiple contagion channels in the banking system focused mostly on combining direct contagion via the solvency channel with indirect contagion from fire sales ([Cifuentes et al., 2005](#); [Nier et al., 2007](#); [Gai and Kapadia, 2010](#)). These models studied numerically the interaction of these two contagion channels using *simulated* interbank networks. The networks are subject to an idiosyncratic shock that hits the assets of one of the banks. If the bank defaults the shock is transmitted to its creditors (direct contagion). Further, as the failed bank's assets are sold at fire sales prices, the shock is propagated in the system via asset prices (indirect contagion). In particular, [Cifuentes et al. \(2005\)](#) built a theoretical model of an interbank network and combined direct linkages with indirect linkages via overlapping asset portfolios of banks. They find that when one allows for endogenous changes in the prices of fire sold assets, initial shocks from the failure of one bank may be amplified in the interbank network, leading to potentially large effects. Both [Nier et al. \(2007\)](#) and [Gai and Kapadia \(2010\)](#) extend their models of direct exposures using the fire sales model by [Cifuentes et al. \(2005\)](#). [Gai and Kapadia \(2010\)](#) find that adding an indirect channel does not alter the robust-yet-fragile property of the original network. [Nier et al. \(2007\)](#) find that market liquidity risk increases default cascades for any level of connectivity (i.e. the probability that a bank has lent to another bank in the network). Furthermore, they find that illiquid asset holdings make concentrated banking systems especially fragile. In a concentrated system, the default of a large bank requires the liquidation of a large amount of assets.

<sup>9</sup>Core-periphery networks contains two type of nodes: nodes in the core and nodes in the periphery. In this model, each node in the periphery has only out-going links to nodes in the core, while nodes in the core are also randomly connected among themselves, and there are no directed links from the core to the periphery nodes.

<sup>10</sup>Collateral 'velocity' is defined as the ratio between total collateral that banks make available for re-use and the initial proprietary collateral that banks can re-use.

	Direct contagion		Indirect contagion
	Solvency	Funding-liquidity	Fire sales (and portfolio overlaps)
Cifuentes et al. (2005)	×		×
Nier et al. (2007)	×		×
Gai and Kapadia (2010)	×		×
Caccioli et al. (2015)	×		×
Roncoroni et al. (2019)	×		×
Aldasoro et al. (2022)	×		×
Aldasoro and Faia (2016)	×	×	×
Montagna and Kok (2016)	×	×	×
Covi et al. (2020)	×	×	×
Covi et al. (2021)	×	×	×

Table 3: Models accounting for the interaction of direct and indirect contagion channels.

This exacerbates asset price contagion for concentrated systems compared with less concentrated systems.

Among early models using simulated interbank networks, [Montagna and Kok \(2016\)](#) is one of the few accounting for three channels of contagion: direct contagion via the solvency channel and funding-liquidity channel and indirect contagion via fire sales. They build an agent-based model where banks can interact with each other through the network. The network consists of three layers: short-term and long-term direct interbank exposures and indirect exposures via overlapping portfolio. They show that the contagion effects when considering the shock propagation simultaneously across multiple layers of interbank networks can be substantially larger than the sum of the contagion induced losses when considering the network layers individually.

Recently, a growing number of papers have analysed these interactions empirically using *supervisory datasets*. [Caccioli et al. \(2015\)](#) show the importance of considering both counterparty and liquidity risk by simulating shocks in an interbank network using Austrian data on direct exposures. The system is resilient to the failure of a single bank if counterparty risk is the only contagion mechanism. Then, they add a theoretical model of indirect interbank linkages based on [Cifuentes et al. \(2005\)](#), where they connect all the banks in the network to a unique common asset. On combining counterparty risk with overlapping portfolio risk, contagion is strongly amplified, resulting in much larger cascading failures than would be observed otherwise. [Roncoroni et al. \(2019\)](#) study the interplay of direct (the network of interbank loans, but also banks exposures to non-financial corporate and retail clients) and indirect contagion (via overlapping exposures to common asset classes) in the EU banking system, using ECB datasets on 26 large euro area banks. They identify a strongly non-linear relationship between diversification of exposures, shock size, and interbank contagion losses. One of the most important finding is that diversification of bank exposures to real economic sectors helps to contain contagion, but diversification of counterparties in the interbank market can increase spreading of contagion losses.

[Aldasoro et al. \(2022\)](#) provide an accounting-based stress-testing framework to assess loss dynamics in a banking sector connected via direct interbank exposures and common asset holdings (i.e. overlapping portfolios) and apply the framework to detailed micro-financial euro area data. They find that interbank exposures account for only a minor share of the overall losses due to contagion. Aside from the direct effect of shocks to the value of assets on the trading book, common exposures that make banks vulnerable to fire sales and synchronous price dislocations account for the bulk of distress contagion.

Further, few papers have studied the interaction between fire sales and both channels of direct contagion, via the solvency channel and the funding-liquidity channel. [Aldasoro and Faia \(2016\)](#) build a network model of optimizing banks featuring contagion on both sides of balance sheets: runs on short term liabilities and banks' liquidity hoarding induce liquidity freezes (direct contagion via the funding-liquidity channel); interconnected debt defaults (direct contagion via the solvency channel) and fire sales produce asset risk. The interaction of these contagion channels can generate amplification effects: liquidity freezes can lead to fire sales, and the resulting fire sales losses can lead to funding runs as investors react to news of bad performance.

[Covi et al. \(2021\)](#) develops a model that also account for these three channels, where banks are subject to

credit and funding shocks and can engage in fire sales. The model is calibrated using euro area banks’ large exposures data and detailed information on banks’ balance sheet characteristics and regulatory requirements. The authors find that losses due to credit risk dominate those due to funding and liquidity risk via firesales. However, illiquidity-driven defaults outweigh by far those triggered due to insolvency. Further, funding risk relative to credit risk is more concentrated on few large exposures whose defaults may trigger a liquidity default event. The authors suggest that it may be prudent to impose limits on the concentration of funding since some small and medium-sized banks are exposed on the liability side to few large banks.

Covi et al. (2020) also account for these three channels to study euro area banks’ systemic risk using the multi-layer framework from Montagna and Kok (2016) and data for European banks. However, they focus on an alternative definition of systemic risk, i.e. the probability of a large number of banks default at a given time, conditional to the information available at the previous time. They empirically estimate systemic risk by subjecting the model to a distribution of shocks coming from the real economy. The results show that the key determinants of systemic risk are the correlation of economic shocks and fire sales.

We conclude by pointing out that collateral channels, which are the relatively newer type of contagion models developed, have been so far mostly studied in isolation. Some models, like Gai et al. (2011), combines direct and indirect contagion from collateral, as the shock originates from collateral but the contagion plays out in the interbank market. Cont et al. (2020) accounts for the increase liquidity needs from margin calls, which can in turn lead to fire sales. However, the model does not explicitly model contagion as there is only one bank. Ghamami et al. (2022) studies collateral fire sales, showing that this price-mediated channel amplifies losses beyond the direct effect of missed payments. Future research could build on these models to account for the interaction of collateral channels with fire sales as well as direct contagion channels in unsecured interbank markets.

## 4 Contagion in the non-bank financial system

The financial system comprises a range of entities often referred to collectively as ‘non-bank financial institutions’ (NBFI) or sometimes simply as ‘non-banks’. This group includes various types of asset managers, insurance providers, and financial market infrastructures. Like banks, these non-bank financial institutions can also contribute to systemic risk.

We begin this section with a brief overview of the main types of NBFI, setting out the roles they play and the traditional structure of their balance sheets. We then examine which of the contagion channels described earlier apply to these entities; we review the nascent literature that has attempted to model these contagion channels, and we point the reader to accounts of historical examples of systemic stress in this sector. Following this, we zoom in on recent advances in models of fund and CCP stress testing. And we finish the section by covering the handful of pioneering models of system-wide stress testing, models that include multiple sectors and their interactions.<sup>11</sup>

### 4.1 Overview of the non-bank financial system

Non-banks can contribute to systemic risk as they carry out traditional non-bank activities, including long term investment management and insurance provision. One recent stress in the financial system occurred when the extent of the spread of COVID-19 became apparent in March 2020. Non-banks were at the heart of this liquidity stress (Eren et al., 2020; Czech et al., 2021; Huang and Takáts, 2020; Hüser et al., 2021). Giese and Haldane (2020) argue that this experience calls for greater routine monitoring of market-based financing vehicles to assess these risks and strengthens the case for applying stress tests to them. There have also been a number of less systemic but no less significant instances of contagion involving the interaction of non-bank entities, either contained within a sector, or resulting in spillovers to other sectors, including to the banking sector.

The risk of contagion is largely determined by the balance sheet structure of NBFI and the connections between institutions. Those factors are influenced by the nature of the activity the particular non-bank undertakes. Financial institutions which do a large amount of intermediation between other financial institutions (such as investment banks and money market funds) are more likely to transmit stress between financial sectors than institutions that intermediate between households and corporates (such as retail banks and some long term investment vehicles), although the latter are clearly important for the transmission of stress to the real economy (see section 5).

Table 4 summarises the key features of the balance sheets of non-banks, focusing on their main business activities.

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<sup>11</sup>There have been complementary attempts to produce comprehensive maps of the non-bank financial sector and interconnections within it – see, for instance, Kashyap and King (2019). Such efforts have so far been hampered by data availability, but also the relative opaqueness of the sector relative to the banking sector, which is more heavily regulated and more closely monitored by supervisors.

Type of firm	Assets	Liabilities	Nature of vulnerability
Defined benefit pension funds and life insurers	Long duration, chosen to match liabilities. Can use derivatives to extend duration.	Long duration or perpetual, often resembling annuities.	Solvency risk. Market risk and credit risk on assets, longevity risk on liabilities.
Defined contribution pension funds and general insurance	Other funds, equities, bonds, holdings of private assets. Typically aims to maximise returns over long time horizons.	Long or medium duration. Value is either directly tied to the assets, or uncorrelated from the assets. Does not drive investment decisions.	Market risk and credit risk on assets. Event risk for insurance companies.
Open-ended investment funds (including MMFs)	Wide range of financial assets, mixed liquidity and quality characteristics. Aims to maximise returns over short horizons.	Shares, often redeemable on demand.	Liquidity mismatch. Sometimes correlated asset portfolios.
Closed-ended investment funds	Wide range of financial assets.	Non-redeemable shares, but can be traded on a secondary market.	Generally limited vulnerabilities.
Leveraged investment funds, including hedge funds	Tend to hold higher quality securities and take speculative or arbitrage positions.	Usually some form of secured borrowing using the assets as collateral.	Market risk and credit risk on assets. Liquidity and solvency risk from use of leverage and derivatives.
Central counterparties	Derivatives and reverse repo.	Derivatives and repo.	None, until a counterparty default.

Table 4: Summary of assets and liabilities of six classes of non-banks

In addition to the traditional assets and liabilities described in table 4, most financial institutions can use leverage, in the form of securities financing transactions (SFTs) and repo, and derivatives as part of their portfolio management or investment strategy. These form another potential channel for distress to spread between institutions. The use of initial margin and variation margin with SFTs and derivatives can transform counterparty credit risk into funding-liquidity risk. When the value of the derivative (or the value of the collateral) changes, one counterparty may immediately owe another some quantity of liquid assets. Failure to pay could result in default. After default, the remaining counterparty may have an unwanted exposure, and so may seize collateral and engage in a fire sale to minimise potential losses. This mechanism of contagion has been illustrated many times.

Non-banks can also undertake the kind of maturity, credit and liquidity transformation that traditionally takes place in the banking sector. When they do this, they are often referred to as ‘shadow banks’ (see [Pozsar et al. \(2010\)](#)). Those activities give rise to similar forms of systemic risk and opportunities for contagion as occur in the banking sector, but often in an environment with less regulation and less transparency. Shadow banking, and non-banks generally, played a major role in the global financial crisis. But few stress testing models have attempted to explore risks in these areas.

## 4.2 Contagion mechanisms between non-bank financial institutions

We begin by describing how different types of distress and contagion might arise from the natural liabilities (i.e. those excluding collateral demands from derivative and leverage) and the traditional assets of non-banks. For the solvency contagion channel, we find less research covering non-banks than banks, because non-banks tend to issue less unsecured debt that is held by other financial sector entities. We also find less research on the funding-liquidity channel, because non-banks do not tend to issue short-term ‘runnable’ liabilities, that is, liabilities that need to be rolled over or raised at short notice. By contrast, we find relatively more research on indirect contagion via the market-liquidity channel, because price moves can be a trigger for action by investors, even when there is limited risk of default. And we find some research (and numerous historical examples) of contagion involving collateral, which can affect any institution that use secured leverage or derivatives.

### 4.2.1 Direct contagion via the solvency channel

For solvency contagion to occur, an institution must have debt or debt-like liabilities on which it can default, and those liabilities must be held by other financial institutions that also have debt-like liabilities.

Within our classification above, defined benefit pension funds, general and life insurance companies, and leveraged investment funds, all have contractual debt-like liabilities and therefore face solvency risks.<sup>12</sup> Of these,

<sup>12</sup>Unleveraged funds and defined contribution pension funds have equity liabilities which, by construction, are equal to the value



the traditional liabilities of defined benefit pension funds and insurance companies tend to be held by natural persons rather than financial institutions, thus limiting the possibility of contagion. Such funds can, however, adopt investment strategies that use leverage or derivatives, either directly themselves or by investing in other funds that use those strategies. Such investment strategies generate liabilities that are held by other financial institutions, thus giving rise to the potential for contagion. These are typically secured with collateral and so the mechanism for contagion is via margin calls and the potential for fire sales, rather than direct solvency contagion (see Section 4.2.4).

As a result, pure solvency contagion outside the banking system is rare, and there is relatively little published work on the subject. One notable historical case, the so-called ‘LMX spiral’, involved the London reinsurance market in the 1980s (see for example [Bain \(1997\)](#) for an account). Reinsurance companies insure the liabilities of general insurance companies, as well as insuring the liabilities of other reinsurance companies. This can help the financial system spread and diversify risk, but it can also lead to opaque interconnections between entities. Long chains, or spirals, of reinsurance contracts can mean that, following an event, the total gross claims within the system can far exceed the initial losses. In the late 1980s and early 1990s, a series of incidents including the explosion of the Piper Alpha oil rig led to large claims on insurance companies which crystallised into very large reinsurance claims.

#### 4.2.2 Direct contagion via the funding-liquidity channel

Funding liquidity usually refers to the ability of borrowers to raise or roll over debt. It can also refer to demand for funding from the use of collateralised derivatives, which we discuss in Section 4.2.4. Here, we focus on short-term unsecured debt or debt-like instruments. Long-term secured or unsecured debt tends not to give rise to contagion risk because the longer maturity gives more time to plan and respond to changing conditions.

As described in Table 4, most non-banks do not issue unsecured debt. Open-ended funds (OEFs) issue equity liabilities that have a deposit-like option to be redeemed, sometimes on demand and sometimes with a notice period. Such redemptions are typically funded by selling assets. The literature on open-ended fund stress testing is more advanced than other sectors, and covered in Section 4.3.1.

Money Market Funds (MMFs) are a special type of open-ended fund, that is typically used for cash management. They issue equity liabilities that have debt-like characteristics, for example MMF liabilities are redeemable on demand, and many MMFs aim to maintain a stable share price of 100 (also called a stable Net Asset Value or NAV). In some cases, maintaining a stable NAV is supported by special regulations that allow them to round the value of their NAV to two decimal places. This makes their liabilities appear debt-like, and investments in MMFs are often used as substitutes for bank deposits.

On the asset side, MMFs invest in short term paper, usually less than one year maturity. There are two main types of MMF. Government MMFs invest in government securities, such as short term government bills and reverse-repo secured on government debt.<sup>13</sup> A second type, often called Prime MMFs, invest in private sector securities, often bank deposits, commercial paper, certificates of deposit, and other short-term money market assets.<sup>14</sup> Unlike other OEFs, MMFs typically hold assets to maturity and fund redemptions through a cash buffer rather than with asset sales. That cash buffer is replenished as assets mature.

The assets held by Prime MMFs can be illiquid and difficult to sell in times of stress, which means those MMFs undertake liquidity transformation and are vulnerable to funding-liquidity risk. If MMF investors attempt to redeem more shares than the MMF has held in overnight assets, the fund can either attempt to sell assets (for which it may receive less than face value) or it may choose to suspend redemptions. If it suspends, then the redeeming investors would not receive the cash they might have expected to. If that cash was needed to make necessary payments, such as to meet a margin call, there could be further knock-on impacts on the wider system.

There have been numerous examples of liquidity risk in MMFs crystallising, see [Bouveret et al. \(2022\)](#) for a history. We are not aware of any models that capture the potential for funding liquidity contagion as a result of redemption suspensions at money market funds. However, [Baes et al. \(2021\)](#) models MMF liquidity, focusing on the effectiveness of different types of regulation at addressing the liquidity mismatch, rather than attempting to model the spillovers or contagion arising from it.

#### 4.2.3 Indirect contagion via the market-liquidity channel

Investment returns can drive flows into, or out of, investment funds or specific assets. The overall mechanism involves initial falls in fund values (from an exogenous shock) leading to redemptions, asset sales, and further falls in fund values and further redemptions. Recent research in this area combines empirical flow-performance relationships from open-ended funds to calibrate fund redemptions, with price-impact metrics on assets to

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of their assets, thus limiting solvency risk.

<sup>13</sup>In the UK and EU these are called Public Debt Constant Net Asset Value (PDCNAV) funds.

<sup>14</sup>In the UK and EU, these are called Low-Volatility NAV (LVNAV) or Variable NAV (VNAV) funds.

calibrate the further falls in asset prices. Overall, this can be built into a stress testing framework for funds (see section 4.3.1 for a detailed discussion of fund stress testing and Tables 5 and 6 for overviews of key papers). Sydow et al. (2021) use a model with this mechanism and combine it with a banking sector to capture additional channels of contagion. The banking sector suffers a hit to solvency from the initial shock, which leads to liquidity hoarding which adds to the redemption pressure on funds. And the asset sales by funds includes sales of bank debt, which increases the funding cost for banks.

On very short time scales, institutions may find themselves involved in fire sales of assets. This can occur if they need to raise cash at any cost (for example, to meet a margin call and avoid default), or if they need to reduce their exposure to potential falls in the value of the asset (for example, if they have just taken ownership of collateral or if they need to unwind a hedge following the default of a counterparty). In the context of non-banks, this usually results from the use of secured leverage or derivatives and is discussed in section 4.2.4. However it sometimes also arises due to highly correlated trading strategies, or ‘crowded trades’, which are all unwound at the same time. One famous example of this is the ‘Quant Meltdown’ of 2007, described in Khandani and Lo (2008).

Another source of price-mediated contagion on relatively short time scales arises from dynamic hedging activity. At the very simplest level, financial institutions that sell options may choose to hedge those exposures dynamically. Hedging strategies can sometimes involve buying an asset as its price rises, and selling an asset as its price falls. Such purchases and sales can sometimes act to amplify price moves, especially if they are not fully anticipated or if market liquidity is thin. This mechanism has occurred numerous times in the past. Perhaps most notably, the sale and associated hedging of so-called ‘portfolio insurance’ products is said to have played a role in amplifying the 1987 stock market crash. The hedging of Power Reverse Dual Currency notes is widely thought to have amplified volatility in Asian FX markets in 2008.<sup>15</sup> Hedging activity doesn’t always involve the hedging of derivatives. In the US, a dynamic known as ‘convexity hedging’ can amplify price moves when long term interest rates approach certain levels. In this example, hedging is driven by the non-linear relationship between interest rates and the value of mortgage servicing rights. We are not aware of any published models which attempt to capture these dynamics in a stress testing context.

Modelling the price impact of asset sales is a crucial component of any stress test model that attempts to capture this channel. That literature is relatively mature, and continues to develop with the arrival of high frequency and granular data on transactions in financial markets. That said, traditional asset price models can struggle to capture dynamics such as fire sales and hedging activity, because those dynamics appear to give rise to low risk arbitrage opportunities which contradicts the efficient-markets hypothesis. However, a rich strand of modelling research has developed using agent based models (ABMs). This modelling approach makes it easier to develop models which allow for prices to deviate from fundamental values due to trading pressures, which in turn can allow for multiple equilibria or unstable dynamics, although those features are not always present. A comprehensive survey of agent-based models used in finance is given in LeBaron (2006). These papers often abstract the investor base into ‘value’ investors and ‘momentum’ or ‘trend’ investors, and explores the dynamics of how those behaviours interact. Farmer and Joshi (2002) is one of the seminal papers, and shows how a combination of trading strategies can amplify noise and cause excess / clustered volatility.

The mechanisms described in this section are also related to broader ideas about risks from procyclicality, which can happen on long timescales and lead to significant macroeconomic feedback effects. We do not cover that literature here, but the interested reader may wish to explore Minsky (1977)’s ‘financial instability hypothesis’, and literature on risk myopia leading to pro-cyclical investor behaviour and herding (Bijlsma and Vermeulen (2016), Rudolph (2011) and Haldane (2014)

#### 4.2.4 Contagion involving collateral

In addition to the assets and liabilities described in Table 4, most financial institutions are able to engage in securities financing transactions (including repo and reverse-repo), and use derivatives collateralised with initial and variation margin.

Derivatives create assets and liabilities whose value is linked to the price of some underlying instrument or index. This means a counterparty exposure can get bigger when market prices change. A growing liability, if not properly hedged (or not hedged at all), could be difficult for the counterparty to repay. After 2008, regulations and market practice moved to increasing the use of collateral to reduce counterparty credit risk. Broadly speaking, there are two types of collateral. Initial margins (or haircuts) refers to an overpayment of collateral by one counterpart in order to take account of potential changes in market prices following default. Variation margin refers to flows of collateral between counterparties triggered by changes in the market price of either the collateral, or the derivative contract which is being collateralised. Failure to pay a collateral call is usually treated as a default event.

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<sup>15</sup>Power Reverse Dual Currency (PRDC) notes were structured products that represent a synthetic version of a carry trade, i.e. borrowing in a currency with a low interest rate and lending in a currency with a higher interest rate, betting that the exchange rate will not follow covered interest parity.

Different institutions use derivatives or securities financing transactions for different reasons, but the consequences for contagion risk are broadly similar. In all cases, the use of collateral reduces counterparty credit risk, and therefore limits solvency contagion. However it introduces funding-liquidity risk as institutions may need to raise funds to meet margin calls. And after a default event it introduces market-liquidity risk as counterparties seek to sell collateral.

There are numerous historical examples of NBFIs in distress and contagion involving collateral.

- Liability-driven investment (LDI) strategies are sometimes used by defined benefit pension funds and life insurance companies in the UK. These strategies involve the use of leverage and derivatives to manage duration risk. Moves in asset prices triggered margin calls on positions during the March 2020 ‘dash for cash’ (Czech et al. (2021)) and during the September 2022 gilt market event. This led financial institutions, including LDI funds, to draw down their cash buffers and to redeem shares from money market funds. In the March 2020 event, this crystallised some of the liquidity mismatch risk within money market funds, and resulted in many needing to sell assets in distressed and illiquid markets in order to fund redemptions.
- Hedge funds often use leverage to amplify returns as part of their investment strategy. Archegos Capital Management was a highly leveraged hedge fund which used derivatives (total return swaps) to gain leveraged exposures in the equity of a small number of companies. When the price of those stocks fell, in early 2021, the fund faced margin calls which it was unable to pay. Following the fund’s default, the bank counterparties sold the assets they held that were hedging their exposure, which moved prices further and resulted in some banks incurring realised losses totalling around \$10 billion. (See for example ESMA (2022) for an account.)
- Another failure of a leveraged hedge fund occurred in 1998. Long Term Capital Management was a highly leveraged hedge fund which had borrowed money from banks to arbitrage small price differences between US treasury securities. When those price differences increased (due to market stress following a sovereign default and the Asian financial crisis), the hedge fund faced margin calls which it was unable to pay. Most of the fund’s counterparties came to a ‘standstill agreement’ whereby they took over the financing of the fund’s positions and held them to maturity, rather than closing them out immediately. (See for example Lowenstein (2001) for an account.)
- In the 2000s, general insurance companies, including AIG, expanded their business model by selling credit risk protection using derivatives. This example illustrates the ability of derivatives to add a new ‘layer’ of contagion risk to a business model which ordinarily would not contribute to systemic risk. (See for example Commission et al. (2011) for an account.)
- There have been several examples of the failure of central counterparties in the past (see Hills et al. (1999)), including most recently the Hong Kong Futures Guarantee Corporation in 1987. This was a CCP that cleared long dated derivatives. Following volatility in market prices, the CCP’s counterparties were unable to meet margin calls, leading to losses for the CCP. The CCP was bailed out by the Hong Kong government for \$1 billion.

There is a growing literature that uses trade repository data to analyse the potential for systemic risk arising from derivatives markets. Ali et al. (2016) performed a pilot study using CDS data. More recently, Bardoscia et al. (2019) describes a model that simulates stress in derivatives markets of the kind described above. Shocks to market prices trigger variation margin calls which lead to payment flows between financial institutions. If the size of those margin calls exceeds the liquidity buffers available to the institution, then institutions will wait to receive payments from others, or borrow cash in the interbank market to fund the shortfall. These models could form building blocks of a system-wide contagion model. But currently we are not aware of any stress testing models that attempt to capture these mechanisms spreading distress from one sector to another.

## 4.3 Sector-specific approaches

We dedicate specific sections to the modelling of fund and CCP stress testing. The modelling of fund stress tests is probably the most advanced compared to other non-banks sectors. Therefore we review fund stress test models and their components in depth. As regards CCP stress testing, we review this separately as CCPs play a very specific role in the financial system which is different from the other non-banks.

### 4.3.1 Fund stress testing

Let us start this section by summarizing a typical scenario for fund stress tests. It commonly starts with an exogenous redemption shock. The fund then reacts by liquidating assets to cover the redemptions. Asset sales can affect the price of the sold assets via the market liquidity channel. This can trigger further losses at the

fund and result in the need for further redemptions. It can also lead to losses at other firms that might hold these assets. If funds withdraw deposits at banks or redeem MMF shares to cover the redemptions, this can lead to funding liquidity shortages at banks and MMFs. In summary, both the market liquidity and funding liquidity channel may lead to contagion to other financial institutions (for general definitions of the market and funding liquidity channels, we refer to Section 2).

Tables 5 and 6 show overviews of the key fund stress test ingredients we just described and how different papers in the literature have modelled and implemented them, where the first one focuses on fund stress test models with only the fund sector and the second on models that include the reaction of other sectors too (typically banks). Other sectors only play a reactive role to the behaviour of funds in this section, which is the key difference from the system-wide models which we review in Section 4.4.

In the rest of this section, we provide more details on the different model ingredients presented in Tables 5 and 6 and on the approaches taken to model them.

<b>Paper</b>	Cetorelli et al. (2016)	Gourdel et al. (2019)	Fricke and Fricke (2021)	ESMA (2019)	Fiedor et al. (2019)
<b>Fund type</b>	U.S. high-yield bonds	Global bond and equity market	US-domiciled domestic equity funds	EU bonds and equity	Global bond and equity market
<b>Shock</b>	Scenario approach: parallel shift of the yield curve of 100bp, holding stock returns constant	Scenario approach: adverse macro-financial scenario	Scenario approach: shock of -5% on all stocks	Historical: redemption shock calibrated using the Expected Shortfall at 1%, 3% and 5% level	Redemption shock
<b>Impact on fund net flows</b>	Flow-return relationship: Current flow = estimated current alpha (from a first stage regression); No estimate published.	Two steps: 1. Bayesian model averaging techniques to project impact of scenarios on country portfolio flows. 2. Impact of country portfolio flows at the individual fund level.	Flow-return relationship: Current flow = Lagged returns and flows.	Direct (as pure redemption shock)	Direct (as pure redemption shock)
<b>Liquidation strategy</b>	Asset liquidation using the slicing approach	Liquidate if AUM drop more than 30%	Asset liquidation using the slicing approach	Compare asset liquidation using the slicing and the waterfall approach	Asset liquidation using the slicing approach
<b>Price impact</b>	Linear price impact	Not modelled	Amihud ratio	Linear price impact	Linear price impact
<b>Second round</b>	Yes	No	Yes	Yes	Yes
<b>Outcome</b>	Spillover losses would be 22 cents per dollar of initial loss.	3.4% of equity funds would liquidate, representing 1.8% of total assets; 3.4% of bond funds would liquidate, representing 0.6% of total assets.	In response to a 5% shock on asset values, aggregate vulnerability (AV, the fraction of equity wiped out due to the fire sale mechanism, relative to total equity) is 1.3%.	Price impact limited for most asset classes. However, for asset classes with more limited liquidity, such as high yield bonds and emerging market bonds, fund sales could have a material impact, ranging from 150 to 300 bps, and generate material second round effects.	Results are an almost linear function of the initial shock, the size of the shocked category of funds, market liquidity (price impact factor), and in the case of second round effects the flow-performance relationship.

Table 5: Fund stress testing models.

Paper	Arora et al. (2019)	Baranova et al. (2017a)
Type of fund	Open ended	Open ended
Other sectors	Broker-dealer and long-term investor	Dealer
Markets	Canadian corporate bond market	European corporate bond market
Shock	Interest rate shock: A parallel shift in the Government of Canada zero-coupon yield curve; Credit spread shock: A rise in Canadian credit spreads by credit quality.	Pure redemption shock based on historical data and judgement
Impact on fund net flows	Flow performance relationship estimated as in Cetorelli et al. (2016); Estimated Flow-performance parameter: 0.4.	Direct as pure redemption shock.
Liquidation strategy	Flexible: framework allows for vertical, horizontal or mixed rebalancing.	Slicing approach by liquidity degree (vertical).
Behaviour of other sectors	The long-term investor solves an expected profit-maximization problem subject to funding constraints by choosing the amount of corporate bonds to purchase from funds. The broker-dealer determines the price discount for corporate bonds and provides financing to the long-term investor.	Hedge fund chooses the proportion of corporate bonds being sold by the fund sector that it wishes to buy; seeks to maximise its profit by balancing (i) the costs of financing its purchase via repo borrowing provided by the dealer against (ii) the profits it stands to make by 'arbitraging' any deviation of the price of the assets from their fundamental value which result from the fund's sale. The dealer clears the market.
Price impact	Based on the partial equilibrium model developed by Baranova et al. (2017b) calibrated to Canadian data to estimate the impact that large investor redemptions would exert on the liquidity risk premium.	Based on the partial equilibrium model developed by Baranova et al. (2017b) estimate the price impact of asset sales of generic investment grade corporate bonds.
Second round	No	Flow-performance estimation: estimate the sensitivity of fund redemptions to returns for each category of funds by running a panel regression, which allows for fund-specific fixed effects (Morris et al., 2017); Estimated flow-performance parameter: 0.5 for fixed income, 0.1 for equity. Those outflows lead to further asset sales and price impacts.
Outcome	Aim is to estimate the liquidity risk premium which quantifies the net impact of the interaction of demand for and supply of immediacy (= speed at which a large buy or sell order can be fulfilled in a particular market).	A level of weekly redemptions from investment-grade corporate bond funds equal to 1% of total net assets would result in an increase in European investment-grade corporate bond spreads of around 40 basis points. Redemptions of 1.3% of total net assets could increase spreads by around 70bp, which is equivalent to 50% of their historical average value. Second-round investor redemptions that occur in response to first-round reductions in performance are found to amplify initial market moves materially, accounting for around half of the overall change in spreads.

Table 6: Fund stress testing models with reactions of additional sectors.

**Definition of shocks.** Fund stress test scenarios typically start with an exogenous redemption shock. The three main methods to calibrate a redemption shock are the historical approach, an event study or expert judgment. For example, the fund stress simulation by ESMA (2019) uses a pure redemption shock calibrated using historical data.

Another option is to model the redemption shock as the result of a macro-financial scenario. The main advantage of this methodology is that results can be aggregated across different fund types, as they are all subject to the same scenario. The main difficulty is however that translating macro-financial shocks into fund outflows is a complex exercise, for which there are two main methodologies.

The first methodology directly estimates the relationship between flows and macro-financial variables. This is based on the assumption that there is a correlation between net flows at the fund level and macro-financial variables of interest. According to ESMA (2019), commonly used macro-financial variables for such an exercise are the expected volatility (VIX or VSTOXX), proxies for credit risk for bond funds (spreads) and measures of the term premium. See for example Bouveret (2017) for an application of this approach.

The second methodology uses the flow-performance relationship. This is a two-step approach. First, the impact of the shock on the returns of the fund is computed, and then, given the projected returns, the net

flows are quantified. In a pioneering paper on fund stress testing [Cetorelli et al. \(2016\)](#) use this method, which has then been picked up by many subsequent papers on the topic, such as [Fricke and Fricke \(2021\)](#) and [Arora et al. \(2019\)](#). Different estimation strategies may be adopted to assess how sensitive the fund’s flows are to performance, [Table 7](#) provides details on the estimation strategies and variables used by different papers. All empirical analyses listed in the table find a positive relationship between funds’ past performance and investor outflows, though the estimates vary depending on the choice of explanatory variables and the sample of funds considered.

Paper	Fund type	Estimate	Explanatory variables	Notes
<a href="#">Fricke and Fricke (2021)</a>	US-domiciled domestic equity funds.	0.3	Lagged returns.	
<a href="#">ECB (2017)</a>	Euro area-domiciled mixed bond funds	0.5	Benchmark indices.	
<a href="#">van der Veer et al. (2017)</a>	Netherlands-domiciled alternative investment funds.	0.04	Lagged returns and flows, leverage, size.	
<a href="#">Morris et al. (2017)</a>	Global bond funds	0.4 (global EME international government bond funds), 0.9 (global EME corporate bond funds).	Lagged returns, change in lagged VIX.	
<a href="#">Goldstein et al. (2017)</a>	Corporate bond funds, equity funds	0.85 (corporate bond funds), 0.41 (equity funds)	Lagged negative returns.	Corporate bond fund estimate also used by <a href="#">Fiedor et al. (2019)</a> and <a href="#">Capponi et al. (2020)</a> .
<a href="#">Mirza et al. (2020)</a>	Euro area domiciled funds	0.2 (equity funds), 0.39 (bond funds), 0.13 (hedge funds), 0.99 (money market funds)	Lagged flows and returns.	
<a href="#">Arora et al. (2019)</a>	Canada-domiciled corporate bond funds	0.4	Change in NAV.	Estimation strategy as in <a href="#">Cetorelli et al. (2016)</a> .

Table 7: Flow-performance factor estimates.

*Note:* An estimate of the flow-performance factor of 0.3 means that a 1 percentage point decline in returns would lead to outflows of 0.3% of the funds’ net asset value (NAV) on average.

**Liquidation strategies.** There are two main approaches to modelling a fund’s liquidation strategy in the face of a redemption shock. The main differences revolve around the type of assets sold, how much to sell of each type and around the timing of the sales (sell different types simultaneously or in a specific order). For a discussion of liquidation strategies for banks see [Section 3.3](#).

Under the slicing approach, funds try to keep the structure of the portfolio constant by selling all securities in the portfolio in the same proportion. Typically the slicing is done by asset class (horizontal slicing), thereby ensuring that the portfolio composition remains the same. The fund might be constrained by its prospectus to adopt this liquidation strategy. In practice, if the shock is equal to 10% of the NAV, funds will sell 10% of each asset class in the portfolio. This is the most commonly used approach in the reviewed models ([Cetorelli et al., 2016](#); [Fiedor et al., 2019](#); [Fricke and Fricke, 2021](#)). This approach emphasizes investor protection, as the fund keeps the portfolio structure identical. Thereby remaining and redeeming investors are treated equally. The potential drawback of this liquidation strategy is that funds investing in less liquid asset classes will have to sell a large amount of these assets. These sales are likely to have a larger price impact than the sales of more liquid assets, which could then have financial stability implications. A related drawback is that the performance of the fund could suffer more due to the larger price impact. The slicing could also be done by liquidity degree of the assets (vertical slicing). This approach is less common in the literature, examples are [Arora et al. \(2019\)](#) and [Baranova et al. \(2017a\)](#).

Under the waterfall approach, funds are assumed to sell the most liquid assets first. The pecking order for this liquidation strategy is cash, investment grade sovereign bonds and investment grade corporate bonds, high yield sovereign bonds, equities and finally high yield corporate bonds. This is different to the vertical slicing approach explained in the previous paragraph, under which the sales are done simultaneously and in proportion to the liquidity buckets. Under the waterfall approach, financial stability risks might be reduced, as the most

liquid assets are sold first. This can limit the price impact of the asset sales. The potential drawback is that the portfolio structure becomes distorted. In addition, there may be a risk of creating a first-mover advantage since remaining investors end up with a less liquid fund.

**Second-round effects** The liquidation of assets by funds may impact markets and investors in such a way that it triggers a second round of stress. This amplification effect operates through two main channels.

The first channel is the funding liquidity channel (see Section 4.2.2 for a general discussion of the funding liquidity channel for non-banks). This impact can be particularly strong when cash is used to meet redemptions, as the cash will typically come from deposit withdrawals at banks or from the redemption of MMF shares. If these withdrawals are large, they may lead to funding liquidity shortages at the fund's debtors.

The second channel is the market liquidity channel (see Section 4.2.3 for a general discussion of the market liquidity channel for non-banks). There are many different ways to estimate the price impact of asset sales (for a comparison with the bank stress testing literature see Table 2 in Section 3.3). The fund stress testing models under consideration here use a linear price impact (Cetorelli et al., 2016; ESMA, 2019; Fiedor et al., 2019) or the Amihud illiquidity measure<sup>16</sup> (Fricke and Fricke, 2021). The price impact of the sales may generate negative returns for the funds holding those assets, leading to additional redemptions from investors and additional asset sales by funds. The flow-performance relationship is often used to quantify the extent of second round outflows, for example by Baranova et al. (2017a).

For both these channels we have highlighted that the second round could entail cross-sectoral contagion. Table 6 showcases models of fund stress testing that include other sectors in the stress simulation to assess how their reactions to the fund behaviour might lead to further amplification of the shock. Other sectors only play a reactive role to the behaviour of funds in this section, which is the key difference from the system-wide models which we review in Section 4.4.

#### 4.3.2 CCP stress testing

CCP stress testing typically assesses whether CCPs have sufficient funds to cover the event that their two largest counterparties fail to meet their clearing obligations. The CCP's funds are made up from initial margin and default fund contributions. This approach is known as 'Cover-2' (CFTC, 2016). This methodology does not take into account the potential amplification of the initial payment shortfalls via network spillovers and contagion effects or the possibility that more than two members could default (Heath et al., 2016). While the literature on CCP stress testing is still in its infancy, there are some models that aim to incorporate a more system-wide perspective into CCP stress tests. For example, Poce et al. (2018) propose a stress test methodology for CCPs that takes into account the propagation and amplification of financial distress through the network of bilateral exposures between clearing members and apply it to a case study of an Italian CCP. They find that network effects substantially increase the vulnerability of the clearing members. Paddrik and Young (2021) propose a methodology for estimating the vulnerability to default by a CCP in the credit default swaps market. They study the direct and indirect effects of non-payment by members and/or their clients through the full network of exposures. Their analysis indicates that conventional stress testing approaches may underestimate the potential vulnerability of the main CCP for this market.

## 4.4 Multi-sector models of the financial system

In this section, we review models of the financial system that include several sectors (at least one bank and one non-bank sector) and where the shock affects the system as a whole.

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<sup>16</sup>See Amihud (2002) for details on the computation of the measure.



<b>Paper</b>	Aikman et al. (2019)	Farmer et al. (2020)	Bookstaber et al. (2018)	Halaj (2018)	Mirza et al. (2020)	Sydow et al. (2021)
<b>Banking sector</b>	Commercial banks, dealer banks	Banks	Dealer banks	Banks	Banks	Banks
<b>Non-banks sector</b>	Hedge funds, money market funds	Aggregate fund sectors (investment funds + hedge funds)	Money market funds, hedge funds, long-term investors	asset managers	funds	Investment Funds
<b>Asset classes traded</b>	Government bonds, corporate bonds, equities.	Tradable assets.	Tradable assets.	Tradable assets.	Tradable assets.	Loans and Securities
<b>Markets</b>	Repo market	Interbank market, repo market, tradable asset markets.	Asset market, funding market.	Tradable assets, repo market, interbank market.	Asset and loan markets.	Intersectoral Loan and Security Markets
<b>Representative sectors</b>	Yes	Yes for non-bank sectors (features a disaggregated banking sector)	No	No	No	No
<b>Shock</b>	Expected credit losses on UK corporate loans and bonds rise by 50 bp, while expected dividend growth declines by 50 bp.	EBA 2018 stress test results	Allows for shocks based on a reduction in funding by the cash provider, a drop in credit worthiness of the bank/dealers, and a redemption shock to the hedge funds.	Liquidity shock (=outflow of deposits or redemptions)	Model translates an initial market shock to bond yields into losses in bank equity and a fall in the valuation of investment fund shares.	Redemptions from investment funds, increased PDs for non-financial corporations (NFC) combined with stochastic NFC defaults as well as an instantaneous stock market shock.
<b>Contagion channels</b>	Fire sales.	Fire sales, funding, collateral, default.	Fire sales, funding runs, default.	Funding, solvency, fire sales.	Fire sales.	Funding, solvency, fire sales
<b>Second-round effects</b>	Yes	Yes	Yes	Yes	No, in the sense that the price impact of the sales does not trigger new redemptions.	Yes
<b>Outcome</b>	When shocks are large, or when headroom relative to constraints is small, the model can generate an adverse feedback loop in which lower asset prices cause solvency/liquidity constraints to bind, leading intermediaries to pull funding, greater deleveraging, pushing asset prices down further.	When markets for institutions' tradable assets are liquid, solvency contagion risk is the most significant mechanism, whereas when markets are less liquid, contagion via asset sales becomes more dominant and amplifies other channels. Adding heterogeneous financial institutions, and in particular non-banks, changes the magnitude of systemic risk.	The reaction to initial losses rather than the losses themselves determine the extent of a crisis. Liquidity requirements have a significant impact on systemic risk and can hence be viewed as an effective instrument to curb the risk of contagious defaults.	Fire sales and the relationship between solvency and funding costs, as well as the relative size of the fund sector amplify the initial funding shocks.	Relative systemicness of funds is materially lower than that of banks in 2017Q4. Systemic importance of funds has increased significantly over time, owing to the increase in investment fund assets and the decline of bank leverage and shift towards holding more loans in recent years.	Financial amplification mechanisms lead to additional sizeable losses within the financial system. Fire sale losses are less relevant for banks than for investment funds which need to meet exogenous redemptions, and have no access to central bank funding as is the case for banks.

Table 8 provides an overview of the key characteristics of the existing system-wide models. Aikman et al. (2019), Hałaj (2018), Mirza et al. (2020) and Farmer et al. (2020) use data to build and calibrate the model, Bookstaber et al. (2018) is a model that could be taken to the data, but is currently simulated without data. All the models include fire sales as a contagion mechanism, some add funding contagion and also allow for default (solvency contagion). The models with only two sectors (typically banks and funds) tend to have disaggregated sectors (Sydow et al., 2021; Hałaj, 2018; Mirza et al., 2020), models with more sectors tend to have representative sectors (Aikman et al., 2019) or a disaggregated banking sector with representative non-bank sectors (Farmer et al., 2020). This can be due to either the lack of data or due to the level of modelling complexity, or both. Bookstaber et al. (2018) is an exception to this and has several disaggregated sectors, however it does not use data currently, mainly because there is no available data at that level of granularity for all the sectors. This highlights the main challenges currently faced for granular system-wide modelling: data availability and modelling complexity.

At present, there is a paucity of models available for analysing the impact of stress scenarios on the non-bank financial system as a whole. We see substantial gains for researchers devoting effort to this endeavor. The efforts to re-regulate banking systems post the Global Financial Crisis has shifted risk to the non-bank sector; analysing policy options to tackle systemic risk in this sector has therefore become an urgent policy priority. We see benefits to both aggregated and disaggregated modelling approaches. Simple aggregate models can focus on interactions between sectors in the non-bank financial system in a tractable way, aiding intuition. But they cannot capture pockets of risk in individual institutions. Disaggregated models can provide a more detailed assessment of risk within as well as across sectors, but they require granular data on asset holdings and interlinkages.

## 5 Feedbacks between the financial sector and the real economy

There are many interlinkages between the financial sector and the real economy. Households and corporates supply funding to banks in the form of deposits and receive funding in the form of loans. Shocks to households' and firms' income, wealth and liquidity may affect their ability to repay their loans and therefore impact the solvency of lenders. The real economy also supplies 'funding' to the non-bank sector, in particular through investing in funds of the various types mentioned above. Such interlinkages have been the subject of a great deal of study within the macroeconomics literature.<sup>17</sup> The intensity of that study increased substantially since the global financial crisis of 2007, but began long before it.<sup>18</sup> Despite this, work incorporating these linkages into detailed system wide models or stress testing frameworks is still in its infancy. With that in mind, the rest of this section will provide a brief and selective overview of the (very broad) literature covering the relevant linkages between the financial sector and real economy, before discussing work on incorporating these linkages into macroprudential stress testing models. The section will conclude with some tentative remarks on the most promising avenues for further work.

### 5.1 Theory

The processes of financial intermediation described above are subject to a variety of frictions such as informational asymmetries, and misaligned incentives between borrowers and lenders (Stiglitz and Weiss, 1981; Holmstrom and Tirole, 1997). Importantly, the effect of these frictions may be exacerbated under certain conditions, for example if there is a fall in the net worth of lenders or borrowers. A rich stream of literature examines what happens when borrowers' resilience (in the form of their net worth, or the worth of the collateral they can put up), declines - akin to the solvency channel described above. This strand begins with the financial accelerator model of Bernanke and Gertler (1989) and the model of credit cycles by Kiyotaki and Moore (1997). Bernanke et al. (1999) extends this work by embedding a financial accelerator type mechanism in a new-keynesian DSGE model. In these models, falls in borrowers' net worth, or the value of their available collateral, lead to a reduction in the quantity of finance banks' offer to them, or an increase in the cost of accessing finance.<sup>19</sup> Other work emphasises constraints on, and shocks to, banks' financial resilience as generating fluctuations in the availability of credit - akin to the funding liquidity channel described above. In the seminal work of Diamond and Dybvig (1983), bank depositors may withdraw funding from banks due to concerns around their solvency, with a knock-on withdrawal of bank lending and drop in economic output. And in the models of Gertler and Kiyotaki (2010) and Gertler and Karadi (2011) - the latter of which is discussed in more detail below - banks' are constrained by an incentive constraint or market discipline condition to maintain a given leverage ratio. A feature of these models is that an exogenous decline in their solvency position causes

<sup>17</sup>For an excellent recent survey, see Claessens and Kose (2018).

<sup>18</sup>For example see the seminal works of Fisher (1933) and Minsky (1982).

<sup>19</sup>Quint and Rabanal (2014) examines the extent to which macroprudential policy can dampen these financial accelerator effects by influencing the spread between lending and deposit rates.

them to deleverage in order to preserve their solvency. Relatedly, regulatory constraints in the form of capital requirements (as opposed to market based constraints) can play a role in determining the supply of finance to the real economy (see [Repullo and Suarez \(2013\)](#) and [Bridges et al. \(2014\)](#) amongst others). Closely related, though more general in scope, is the work on ‘leverage cycles’ (see [Geanakoplos \(2003\)](#) amongst other papers).

## 5.2 Empirical evidence

This section provides a brief overview of empirical studies which attempt to quantify the importance of the channels described above, with a view to identifying which channels may be the most important ones to include in macroprudential stress testing models.

### 5.2.1 The bank resilience channel

There are a considerable number of studies which attempt to trace the impact of changes in bank solvency on their supply of credit. Some earlier work on the strength of the relationship between bank solvency and loan supply found that it was statistically significant, but still relatively small ([Bernanke et al., 1991](#); [Berrospide and Edge, 2010](#)). More recent work refines that view by examining under which conditions this channel may be larger or smaller. In particular [Jiménez et al. \(2012\)](#) use micro data on loan applications to disentangle the relative importance of the strength of banks’ balance sheets on loan supply, as distinct from effects through the strength of borrowers’ balance sheets on loan demand (as discussed below). They find evidence that higher short term interest rates or lower GDP growth reduce the supply of credit, that the effects are stronger for banks with weaker capital or liquidity positions, and that these effects are quantitatively important. Consistent with this, [Carlson et al. \(2013\)](#) find a significant relationship between capital ratios and bank lending, and document a stronger relationship between capital ratios and loan growth for banks which are deleveraging than banks which are expanding, and a stronger relationship for banks with lower capital ratios. Relatedly, [Kashyap et al. \(2010\)](#) show that the steady state impact of increases in capital requirements on lending spreads is likely to be negative but modest under normal circumstances, and [Bahaj et al. \(2016\)](#) find empirical support for a model under which the response of lending to changes in capital requirements is ambiguous in sign, and depends on prospects for profitability and lending growth. Finally, some studies find that though bank lending overall does not decrease following a negative capital shock, the composition of bank lending may shift towards lower risk weighted loans ([Bidder et al., 2021](#)), or towards more collateralised lending ([Degryse et al., 2021](#)).

### 5.2.2 The borrower resilience channel

The empirical literature on this channel is on the whole more recent, and more sparse, than on the bank resilience channel. [Mian et al. \(2013\)](#) document a higher marginal propensity to consume out of housing wealth for households that are more levered or have lower incomes, using US data at the zip-code level. They note that this finding could be driven by a range of possible channels, including that these households become more credit constrained as housing wealth (thus the value of the collateral they can borrow against) falls. They find some additional empirical support for this hypothesis, in that changes in indicators of credit constraints are larger for households with higher leverage or lower income for a given fall in housing wealth. On the corporate side, [Fazzari and Petersen \(1993\)](#) show that corporate investment is highly correlated with cash flows, and particularly for small firms, indicating financial imperfections and strength of corporate balance sheets play an important role in investment. More recently, and consistent with this work, [Joseph et al. \(2020\)](#) document the positive relationship between small and medium enterprises’ (SME) cash holdings and investment, consistent with borrowing constraints playing a role in investment decisions for such firms.

## 5.3 Incorporating macrofinancial feedbacks into macroprudential stress testing models

Compared with models of inter-bank contagion and even financial sector contagion, the academic literature on incorporating these real economy feedbacks into macroprudential stress testing models is still relatively nascent ([Gai and Kapadia, 2019](#)), ([Adrian et al., 2020](#)). In particular, relatively few papers incorporate the financial frictions discussed above into a model with a fully fledged banking system in which bank and borrower resilience can interact and produce feedback effects. This section will review the literature that does exist, splitting into three broad categories organised by their modelling approaches: DSGE models, semi-structural econometric models (namely structural and global VARs), and finally network models. [Table 9](#) gives a brief overview of the pros and cons of these approaches, together with some suggestions about how to make these models more useful for informing policy and stress testing.

Approach	Pros	Cons	Next steps for use in informing policy
<b>DSGE</b>	Well developed literature which demonstrates these models can elegantly capture a variety of macro-financial feedback effects. Responses of agents grounded in optimising and rational behaviour.	Requirement of keeping models tractable usually results in highly stylised balance sheets. Many of the models are calibrated rather than fully estimated. And they are typically unable to capture heterogeneity across banks, and cannot be easily extended to examine interconnections between them.	Developing models which could be used to run full macroprudential stress tests would require introducing heterogenous banking agents that could differ in their starting capital positions and sensitivity to shocks.
<b>Semi-structural</b>	These models can be adapted relatively easily, both to suit the data available in practice, and to focus on features of particular importance or interest.	Particularly detailed models may have many separately estimated equations, meaning the overall robustness of the model is questionable. Many do not include an explicit role for changes in banks' asset mix or quality over time, with the result that such changes would only be captured gradually, and implicitly, via their influence on the parameters governing bank sensitivity to macroeconomic shocks.	In order for models to be useful in informing microprudential policy in addition to macroprudential policy, the sensitivity of bank capital to shocks needs to be estimated at the asset class level (and then aggregated to bank level), rather than being estimated directly at the bank level, so that changes in bank's balance sheet composition and thus their resilience could be assessed in a timely way.
<b>Network models</b>	Ideally suited for examining the structure of interconnections between the financial and real sectors. In principle able to model much richer and more detailed balance sheets than most of the models described above.	Typically rely on strong assumptions to determine banks' behavioural responses and their impact. In practice such models often use network reconstruction methods to circumvent the need for detailed balance sheet data.	With the increasing availability of detailed counterparty level data (eg. through the FCAs product sales database, or through trade repositories for derivative transactions), it is possible that more detailed network type models could be constructed in future. Such models - if detailed enough - could incorporate a broad range of interconnections between financial and real sectors, and may eventually be usable in fully-fledged quantitative stress testing exercises.

Table 9: Overview of modelling approaches and their usefulness for macroprudential stress testing

### 5.3.1 DSGE models

These models follow most directly from the theoretical models of real economy feedbacks described briefly above, and offer the familiar advantages of DSGE models in terms of featuring rational and optimising behaviour in the face of uncertainty as microfoundations. However they also come with significant drawbacks. The need for simplicity in order to make them tractable often results in requiring highly stylised balance sheets and behavioural assumptions. They typically include the banking sector as a single representative agent, with the result that such models are unable to capture heterogeneity across banks, and cannot be easily extended to examine interconnections between them. Furthermore, many such models either completely rule out the default of agents in equilibrium, or do not allow for aggregate default rates to fluctuate in response to shocks.<sup>20</sup> This makes them unsuitable to examining bank's responses to severe macroeconomic shocks where many agents may default simultaneously. As such, these models have so far been too stylised to be used as a starting point for fuller stress-testing models. Nevertheless, they are worth reviewing here given they have shed significant light on how financial frictions can give rise to real economy feedback effects, and it may be fruitful to consider how such insights can be captured within macroprudential stress-testing models as they develop further. And, as discussed in more detail below, newer DSGE approaches which allow for heterogeneity across agents may be better suited as a basis for stress test models.

Building on the work of [Bernanke et al. \(1999\)](#) and others described above, several authors built or extended DSGE models shortly following the financial crisis, in an attempt to shed light on some of the questions it raised (notably including [Christiano et al. \(2010\)](#), [Gerali et al. \(2010\)](#), [Meh and Moran \(2010\)](#), [Gertler and Karadi \(2011\)](#), [Paries et al. \(2011\)](#) and [Clerc et al. \(2015\)](#)). Table 10 provides a short summary of some of the main contributions to this literature. The models share many common features, but differ in a few important respects. In the models of [Meh and Moran \(2010\)](#) and [Gertler and Karadi \(2011\)](#) bank behaviour is pinned down by an endogenously determined constraint on banks' leverage ratios, whereas in [Gerali et al. \(2010\)](#) and [Paries et al. \(2011\)](#) it is determined by an exogenous capital target or requirement. Estimation of parameters in these models is generally done using Bayesian methods. However many of the models discussed here are either not estimated at all, or at least not fully estimated, with common practice being to use parameter values

<sup>20</sup>The model of [Clerc et al. \(2015\)](#) is a notable counterexample in this respect.

matching those found or used in other studies, or setting parameters in order to generate plausible outcomes in the steady state or to match empirical priors. The models differ in the number and type of financial frictions incorporated, with some including financing frictions for households, firms and banks, whereas others feature just one or two of these frictions. Most, but not all models feature a monetary component, with nominal rigidities in one or more sectors, and a central bank policy rule. In [Clerc et al. \(2015\)](#), the monetary side of the standard DSGE model is dropped completely, but the model features debt contracts of three types of agent and their associated frictions. In general, the financial frictions included in these models better allow them to generate large cyclical deviations from trend than standard DSGE models. The overall strength of these effects are reasonably consistent across models, reflecting their underlying similarity, and relatively modest – typically a 5 percent fall in intermediary (or bank) net worth in these models produces a fall in GDP of around half a percent.

More recent work includes [Darracq Pariès et al. \(2016\)](#) and [Darracq Paries et al. \(2019\)](#), which improve or extend the basic DSGE models described above, the first by using a detailed portfolio optimisation scheme and information on the cross-section of banks to inform parameters governing bank behaviour in the DSGE model, and second by building a two country version of the DSGE model, with financial and trade interlinkages across countries. Finally, [Kick et al. \(2020\)](#) estimate the empirical elasticity of loan supply in response to changes in capital, using a methodology similar to that in [Carlson et al. \(2013\)](#), and incorporate this empirical finding in a DSGE model based on that introduced by [Gertler and Karadi \(2011\)](#).

Though these models are able to elegantly capture macro-financial feedback effects, their usefulness for informing policy is questionable at present. Developing models which could be used to run full macroprudential stress tests would require introducing heterogenous banking agents that could differ in their capital positions and sensitivity to shocks, and a way to improve confidence around the calibration of key parameters (where they are calibrated rather than estimated). Given these dual challenges, the most promising frameworks may be those where some features (such as nominal frictions) are abstracted away from, in order to allow greater richness in how banks are modelled without the models becoming intractable.

Another possible approach that may hold promise is that of Heterogenous Agent New Keynesian (or HANK) models, a particular class of DSGE models. Recent work by [Hedlund et al. \(2017\)](#) and [Kaplan et al. \(2020\)](#) introduce financial frictions into such models, an important first step towards building fully fledged models that could be used for macroprudential stress testing.<sup>21</sup> Approaches such as these may more able to capture the effects of financial frictions on macroeconomic outcomes than traditional DSGE models, because of their ability to incorporate the distribution of income and wealth across agents and trace how this influences the effects of such frictions.

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<sup>21</sup>It is worth noting that these papers differ in their conclusion as to the overall importance of such frictions in their models.

Paper	Calibration/estimation	Agents	Banking sector	Feedback effect - qualitative	Feedback effect - quantitative
Christiano et al. (2010)	Estimated: Parameter values estimated using bayesian techniques, with value of priors determined by evidence from empirical literature.	Households, entrepreneurs, capital producers, final good producers and a central bank.	Banks lend to entrepreneurs, and create safe liabilities bundled with liquidity services, which are held by households. Banks are constrained only by a reserve ratio.	Two financial frictions in the model: i) a financial accelerator channel and ii) a bank funding channel, governed by shocks to household liquidity preferences, and banks' ability to produce liquid safe liabilities.	In the 'baseline' model news about the riskiness of entrepreneurial returns accounts for 26-47% of output variance depending on frequency and country. The model estimates that in general the bank funding channel is of limited importance, however the model assigns large weight to it during the financial crisis, attributing between 0.3-1.5pp of the total fall in US GDP growth to it.
Meh and Moran (2010)	Calibrated: Parameter values chosen so that the model generates plausible results, or to match findings of, or benchmarks used in, previous studies.	Households, entrepreneurs and banks. Intermediate and final good producers, and a central bank.	Banks lend to entrepreneurs and are financed by net worth and deposits. Banks are constrained by a market discipline condition which resembles a leverage ratio.	Entrepreneurial and bank net worth both play a role in the model. A fall in banking sector net worth reduces loan supply and thus reduces entrepreneurial net worth. The channels in the model operate primarily through quantity rather than price effects.	A bank capital shock of 5% produces 0.5% peak fall in output relative to steady state.
Gerali et al. (2010)	Mixture: Some parameters calibrated in order to pin down steady state conditions in the model, others estimated via Bayesian methods.	Patient and impatient households and entrepreneurs. Capital goods producers, intermediate goods producers, and monopolistically competitive retail goods producers. A monopolistically competitive banking sector split into branches and a central bank.	Banks offer loans to households and entrepreneurs, each subject to an LTV type constraint. Banks have a degree of market power in setting loan and deposit rates, and face quadratic adjustment costs when changing these. Banks target leverage.	The primary friction is that banks' capital positions impact the quantity and price of loans supplied.	A bank capital shock of 5% results in fall in output of 0.5% at year 3 (vs steady state), under the 'high' penalty for being away from target capital ratio. The paper also examines effects of monetary policy and productivity shocks, both of which have a relatively small effect on bank capital.
Darracq-Paries et al. (2011)	Mixture: Some parameters calibrated in order to pin down steady state conditions in the model, most estimated via Bayesian methods.	Patient and impatient households and entrepreneurs. Retailers, distributors and capital and housing stock producers. An oligopolistic banking sector split into branches. A government and a central bank.	Banks lend to impatient households and entrepreneurs, and have a risk-based capital target. Banks set rates in a staggered manner, and have a degree of market power in setting loan and deposit rates. This generates imperfect pass through of changes in the policy rate to lending and deposit rates.	Model features several financial frictions arising from households, entrepreneurs and banks. Loan spreads act as the stabilising force in the model. In response to falls in bank capital they increase such that retained earnings rise, eventually restoring banks' capital positions to target.	A 1pp bank capital shock leads to higher loan spreads and results in a small but persistent impact on GDP - at the lower end of the range of empirical estimates cited by the authors (0.1 to 1pp).
Gertler and Karadi (2011)	Calibrated: Parameter values chosen to match previous academic studies, or are chosen to deliver plausible model features.	Households (comprised of workers who supply labour, and bankers who own financial intermediaries). Three types of firms (producers of capital and intermediate and retail goods), as well as a government and a central bank.	Banks lend to intermediate good producing firms and face an endogenously determined constraint on their leverage.	The primary friction that features in the model is that financial intermediaries' net worth affects their ability to raise deposits and thus affects the supply of loans.	A 1% decline in intermediary net worth produces a peak 0.15% fall in output relative to steady state.
Clerc et al. (2015)	Calibrated: Most parameter values taken from Gerali et al (2010) and Darracq-Paries et al. (2011).	Patient and impatient households, entrepreneurs and bankers (both of whom are finite life), and banks, capital goods and housing producers, and consumption goods producers.	Banks issue deposits and lend to households and firms. Debt is non-state-contingent and all three agents may default on their obligations in equilibrium. Banks face a risk-based capital requirement, which varies countercyclically.	Nominal rigidities are not present in the model. The size of the amplification effects differ markedly depending on the level of capital requirements.	Under the baseline parameterisation a 1std shock to bank risk produces a 0.5% fall in GDP. A 1std shock to housing and physical capital values produces a nearly 1.5% fall in GDP.

Table 10: Overview of DSGE models

### 5.3.2 Semi-structural models

A second strand of literature focusses on building macroeconomic models, using reasonably standard GVAR or SVAR models of the real economy as a first component, but incorporating a banking sector as an additional component. In these models banking sector profits are affected by macroeconomic variables such as GDP and interest rates, and in turn the banking sector has an impact on macroeconomic conditions through the aggregate quantity and pricing of loans supplied. A strength of these models is that they can be adapted relatively easily, both to suit the data available in practice, and to focus on features of particular interest. This means that they may be well suited to examining a range of macroprudential policy questions, such as whether countercyclical buffers can effectively dampen banks incentives to delever in response to a shock. Though the models discussed below are similar in their overall structure, they differ substantially in the features of the banking system they capture, and which they abstract away from. Table 11 provides an overview of some key approaches.

Early work in this vein includes Gray (2013), which introduces a GVAR model consisting of five variables per country (GDP and credit growth, as well as aggregate risk indicators for the banking, corporate and sovereign sectors which are derived from contingent claims analysis), across 16 countries. The model can be used to examine how shocks to banks' risk affect credit growth and in turn GDP. Gross et al. (2016) build on this framework by introducing a GVAR model which includes a more detailed banking sector - including loans, loan and deposit rates, a leverage ratio and a bank probability of default. The model can be ran with an aggregated banking sector for each country or on an individual bank basis.

More recently, Krznar and Matheson (2017) develop a macroeconomic model incorporating a banking sector. The banking sector's net profits are affected by the development of economic variables, which are in turn influenced by credit supply. And credit supply is in part determined by how much capital banks hold versus their requirements. Individual banks in the model differ in terms of their starting capital resources and their capital requirements, but are constrained to have the same sensitivity to shocks. In particular no allowance is made for differences in banks asset composition or quality. A drawback of the model is that since banks cannot issue equity, in order to restore capital positions to target after a shock, they are assumed to be able to take actions which improve their net profits, without having any other damaging effect (motivated for example by actions such as cutting staff bonuses). A more detailed specification might impose limits on such actions, or explicitly include other important defensive actions (eg. raising lending rates or deleveraging), which may have knock on effects on other agents or the wider economy.

The work of Budnik et al. (2020) and Catalan and Hoffmaister (2020) can be seen as extensions or expansions of the schema developed by Krznar and Matheson (2017). The model of Budnik et al. (2020) incorporates a richer balance sheet structure - loans are subdivided into those to households, corporates, and governments. The level of heterogeneity in terms of banks' behavioral responses is also somewhat richer - though the panel estimation procedure results in many parameters being common across banks. The model is also able to distinguish between shocks to loan supply and loan demand. However the level of richness does have drawbacks - many of the equations in the model are estimated seperately and a large number of coefficients in the equations are statistically insignificant, meaning the overall robustness of the model is questionable. A particular example of this is that the equations governing the quantity of loans supplied, and those governing the spread banks charge on loans, are estimated seperately - whereas in reality it seems much more likely that banks take joint decisions across these two variables, as the authors themselves note. In contrast, the work of Catalan and Hoffmaister (2020) is somewhat less ambitious in terms of richness of the balance sheet structure, and therefore likelier somewhat more robust in terms the estimation of its parameters. In particular, there is only one class of loans within the model.

Despite the richness of these models, some feedback effects that would ideally feature are not present. For example, in the model of Budnik et al. (2020) funding costs do not depend on banks' solvency positions, and are largely exogenous. In addition, though borrower demand is linked to macroeconomic variables, there is no explicit role for borrower net worth or collateral availability to influence the supply of finance. Given the considerable size and sophistication of these models, expanding them further to incorporate such channels is likely to come with significant challenges. A particular issue in attempting to apply these models to practical applications or use them in policy setting is that most do not include a role for changes in banks' asset mix or quality over time. Such changes would then only be captured gradually via their influence on the parameters governing bank sensitivity to macroeconomic shocks, with the result that the models are more suited in assessing average bank resilience and strength of feedback effects, rather than its evolution over time. Nevertheless this class of models currently hold the most promise in terms of providing a platform for macroprudential stress testing robust enough to inform the quantitative setting of policy in the near term.

Early applications of these more detailed frameworks has begun to reveal the challenges of fully incorporating macro-financial feedbacks within existing (largely microprudential) stress testing frameworks, as well as the potential for them to generate fresh insights. Budnik et al. (2019) presents a macroprudential stress test of the euro-area banking system using the model more fully laid out in Budnik et al. (2020). In doing so it shines a light on one interesting challenge to be overcome when attempting to integrate such models with microprudential

stress tests. The design of scenarios for such tests typically draw on historical data of economic shocks - which in turn incorporate the historic effects of banking sector to real economy feedbacks. Therefore these shocks are likely already consistent with some level of deleveraging by the banking sector. The authors choose to assume that only the non-linear component of deleveraging in the model is not already implicitly captured in the initial shock and examine the effects this 'excessive' deleveraging has in terms of amplifying the initial shock. [Catalan and Hoffmaister \(2020\)](#) points out a similar challenge - noting that initial macroeconomic shocks can always be scaled up or down in overall severity in order to account for the absence or inclusion of macrofinancial feedback effects in stress testing models. Importantly though they note that the distribution of losses across banks changes substantially in their model depending on whether feedback effects are included or not, even if the aggregate losses and macroeconomic outcomes are constructed to be similar, revealing the potential importance of accounting for feedback effects.

Finally, the models shed light on the possible tension between micro and macroprudential objectives in stress situations. In the model presented in [Budnik et al. \(2020\)](#) banks' capital ratios fall by less in aggregate when bank deleveraging occurs, whereas in the model of [Catalan and Hoffmaister \(2020\)](#) some banks ratios fall by more if deleveraging is allowed to occur, and some by less. In both models this deleveraging comes at a substantial cost in terms of falls in output versus its counterfactual level under simulations where deleveraging is assumed not to occur. The exact conditions under which deleveraging may in aggregate be self-defeating for the banking sector is an interesting question for future research, and one which has great relevance to policymakers balancing both micro and macroprudential objectives.

### 5.3.3 Network models

In contrast to DSGE models, network models are ideally suited for examining the structure of interconnections between the financial and real sectors, and how the structure of the network these interconnections form may propagate or amplify stress. They are also more flexible, and able to model richer balance sheets than the models described above - albeit in practice they often use network reconstruction methods to circumvent the need for detailed balance sheet data. They are however less well suited to examining the behavioural responses of agents, given most of them examine a network of exposures at a single point in time. Where behavioural responses are incorporated in these models, they tend to rely on ad-hoc assumptions governing the impact of such behaviour. The feedback effects that the models discussed below give rise to are quite strong - with losses typically ranging from 2-10 times the initial shock - though given the assumptions that need to be made to arrive at these results, such models may be better suited to showing the qualitative features of amplification and contagion than to giving precise quantitative estimates.

[Anand et al. \(2013\)](#) develops a detailed network model, composed of domestic banks, overseas banks and domestic firms. The connections between these entities are determined probabilistically using network reconstruction techniques, informed by various data sources, including on the aggregate exposures of banks. Banks are assumed to take defensive actions - namely deleveraging and fire sales - once half of their capital resources are depleted. How these loss distributions vary with the size of the initial shock, and key parameters which govern the strength of feedback effects, can then be explored. The strength of the model is its flexibility and tractability - it can generate useful qualitative insights into how the system under consideration responds under different assumptions, with limited need for detailed balance sheet information. However, as a large number of crucial parameters in the model must be fixed by assumption, the model is not designed to be able to support the setting of policy in a quantitative manner. Moreover, given the reliance on reconstruction rather than actual data on interconnections, the model is ill suited to examine how the robustness of a given system varies over time. [Castrén and Rancan \(2014\)](#) and [De Almeida \(2015\)](#) develop similar network models, however both are specified at the sectoral level, and are cross-country. In these models contagion occurs mechanistically through falls in equity prices and their effect on sectoral balance sheets, rather than being driven by the behaviour of particular agents.

Though at present such models are a long way from being useful to inform policy in a quantitative manner, with the increasing availability of detailed counterparty level data (eg. through trade repositories for derivative transactions), it is possible that more detailed network type models could be constructed in future, of the type developed in [Anand et al. \(2013\)](#) but utilising actual data rather than employing network reconstructions. Such models - if detailed enough - may eventually be usable as fully-fledged quantitative stress testing exercises, which could (data permitting) incorporate a broad range of interconnections between financial and real sectors.

### 5.3.4 Other approaches

In a recent paper, [Halaj and Priazhkina \(2021\)](#) develop a game-theoretic stress testing model, where banks' decisions over whether to reduce lending or sell securities is determined by profit maximisation, subject to regulatory constraints as well as individual bank characteristics. Banks' decisions affect one another through the expected return on new lending and securities holdings. A particularly attractive feature of the model,



which merits its inclusion in this survey, is that parameters governing the market impact of individual bank decisions are estimated empirically rather than being set on an ad-hoc basis. However, as the authors note, the model does not feature a fully ‘closed’ feedback loop, in the sense that reductions in lending do not have macroeconomic consequences in terms of output or higher levels of default. If its existing attractive features could be preserved, then extending the model in this way would result in a very promising model for use in conducting macroprudential stress tests. More generally the game-theoretic paradigm is a potential fruitful, though little explored, avenue for further work, given its suitability for capturing strategic and behavioural responses of agents and their effects on each other.

Gross (2022) introduce a macrofinancial model which contains many of the feedback channels of interest discussed above, in a relatively simple and tractable framework which draws inspiration from approaches used in agent-based modelling. A simple set of equations governs the behaviour of agents, with the aim that the model is able to reproduce a number of stylized facts of particular interest. Such approaches can generate useful qualitative insights, though whether they will eventually be deemed robust enough to help set policy in a quantitative manner remains an open question.

Paper	Estimation and data	Variables	Banking sector	Feedback effect - qualitative	Feedback effect - quantitative
Gray et al. (2013)	Largely estimated, with some parameters calibrated. Country weights are estimated (rather than being based on trade weights). Monthly data from 2002 to 2012.	16 countries, with 5 variables per country: GDP and credit growth, plus risk indicators for sovereigns, corporates and banks.	Banking sector is an aggregate and summarised in the main model only by the risk indicator. No explicit behavioural responses are included within the model, though reductions in credit supply as a result of heightened bank risk are captured implicitly.	Feedback channel is through credit supply quantities only (interest rates do not feature in model).	Shocks are not orthogonalised, with scenarios drawn from a conditional tail of the shock distribution. A 664bps shock to the Italian banking sector expected loss variable (with correlated shocks to other variables) results in a 0.5 percent fall in Italian GDP.
Gross et al. (2016)	Estimated using iteratively weighted least squares. Various exclusion restrictions imposed in order to facilitate estimation. Uses quarterly data 1999-2014.	28 countries and 42 individual banks. 4 variables in country cross-section, 5 in the bank cross-section, and 1 in the central bank cross-section.	Bank cross section includes credit, loan rates, deposit rates, leverage and a probability of bank default. Banks have a target long run capital ratio.	Model features both quantity and price of credit. The model can be run with different identifying assumptions for the source of capital ratio shocks (corresponding to deleveraging or capital raising scenarios).	Differs substantially across countries and by assumptions on shock type - GDP response to the standardised positive capital shock is positive in some countries and negative in others (for each of three behavioural assumptions).
Krznar and Mathe-son (2017)	Mostly estimated via Bayesian techniques, with a few select parameters calibrated. Brazilian data, quarterly from 1999-2016.	Single country model with six individual banks included.	Bank income statement items are linked to macroeconomic variables and financial conditions through individual panel regressions. Banks' credit supply is determined in part by their capital surplus to requirements. Banks are assumed to be able to adjust net income in order to restore capital positions to target in the baseline model.	Feedback channel is through credit supply quantities. Feedback channels can be turned on or off. Banks' ability to adjust net income to restore capital levels can also be turned on or off.	1 percent fall in bank capital results in fall in 6 percent fall in credit and 0.5 percent fall in GDP.
Budnik et al. (2020)	Large number of parameters, estimated by a variety of techniques.	19 countries and 91 individual banks.	Detailed balance sheet. Lending is broken down into asset classes and geographies. Bank funding is broken down into wholesale funding and various types of deposits. The cost of each of these liabilities can vary in the model, but the mix of them does not.	Feedback effects occur through both loan supply and lending rates. The model can be run under 'static' or 'dynamic' balance sheet assumptions, with the former precluding the option for banks to deleverage. Banks' CET1 resources fall by more under static balance sheet assumptions in aggregate, but their CET1 ratios fall by less.	Allowing for feedbacks as a result of excessive deleveraging, euro area output falls by an additional 1.6 pp (on top of original 2.4% shock in original scenario).
Catalan and Hoff-maister (2020)	Mixture - some calibrated parameters, in particular governing some of the bank behavioural rules such as interest rate pass through, dividend payouts, etc. Applied to Indonesia using quarterly macroeconomic data from 1990 to 2018 and data on 118 banks from 2001 to 2015.	Single country model (plus external block which is exogenous). Twelve individual banks are included in the model.	Both credit and market losses are considered in the model, though there is only one class of loans permitted. Funding costs for individual banks are allowed to depend on bank specific factors.	Feedback effects occur through both loan supply and lending rates in the model. Since individual bank funding costs are allowed to depend on bank characteristics, a solvency-liquidity interaction is also captured. Lending in the model is a function of changes in banks' fundamentals (including capital ratio versus requirement), with quadratic terms included in order to capture non-linear effects. The model can be run under 'quasi-static' or 'dynamic' balance sheet assumptions, with the former precluding the ability for banks to deleverage.	Allowing for deleveraging results in much smaller (roughly 5pp) peak fall in the aggregate capital ratio, but with the result that real GDP begins to undershoot its level in the 'quasi static' simulation, with a substantial ( 5%) gap by the end of the simulation horizon.

Table 11: Overview of semi-structural models

## 6 Outputs from system-wide modelling

In this section, we review the different types of outputs that a macroprudential stress testing methodology may deliver. We first review the use of balance-sheet based indicators; we then showcase policy-relevant applications for monitoring and calibrating regulatory requirements.

### 6.1 Balance Sheet-Based Indicators

#### 6.1.1 Network measures

The structural features of the banking system can be captured particularly well by a network representation, therefore network measures can be simple but effective indicators for summarising the contribution of financial institutions to systemic risk. The nature of these relationships may be represented via the asset side of an institution’s balance sheet such as its portfolio of loans and securities, or the liability side such as its debt and equity securities issued as well as the amount of loans-deposits received (secured and unsecured).

The most relevant set of network measures used in the literature are summarized in Table 12. The first set of indicators based on centrality measures capture firms’ position in the network, thus allowing for a detection of key players. These indicators reflect information on both sides of the balance sheet, treating equally asset and funding exposures. They are entity-specific indicators, and therefore represent a micro-prudential perspective of risk. Nevertheless they are also used in the calibration of macro-prudential buffer requirements such as the global systemically important bank (GSIB) buffer in order to tackle the issue of *too-central-to-fail* (Covi et al., 2018).

The second set of indicators captures the level of market concentration. A standard measure is the ‘weighted degree’, which captures the total amount of exposures lent (out) or borrowed (in) by each entity in the network. This measure is suitable to provide information regarding the degree of concentration risk as well as the ‘too big-too-fail’ issue. In this respect, a more refined indicator is the Herfindahl-Hirschman Index (HHI), which ranges between 0 and 1, and measures market concentration.

The third measure aims to assess connectivity, i.e. the structure of the network, which often has implications for the transmission of shocks via bilateral exposures. The interbank network has been characterized by a core-periphery structure with low density, in which institutions with high centrality measures tend to provide liquidity to peripheral institutions (Covi et al., 2021). In fact, the relationship between the degree of interconnectivity and financial instability seems to be non-monotonic – that is, high interconnectivity helps to stabilize the system conditional on small shocks occurring, while for large shocks high interconnectivity amplifies the initial impact (Georg, 2013). This measure can be useful to macroprudential supervisors to monitor the speed of shock transmissions in the system.

Network Indicators	Type	Indicator	Source	Perspective
Centrality	Entity-Specific	PageRank; Eigenvector Centrality	Yun et al. (2019); Page et al. (1999)	Micro
Concentration	Entity-Specific	Weighted degree; HH index of market share concentration	Minoiu and Reyes (2013)	Micro
Connectivity	Network-Specific	Network density	Georg (2013); Ladley (2013); Battiston et al. (2012); Nier et al. (2007)	Macro

Table 12: Network Indicators

#### 6.1.2 Model-based measures

The most relevant set of model-based risk measures developed in the literature are summarized in Table 13. They are divided between micro and macro prudential indicators, that is, the former provides information on a entity-specific risk, while the latter on the level of risk in the system.

A first well-known measure – which is actually an enriched version of the centrality measures discussed above – is DebtRank developed by Battiston et al. (2012). DebtRank takes into account in a recursive way the impact of the distress of one or more institutions to their counterparties across the whole network. A high value of DebtRank corresponds to a more central location of the node and is used to determine the systemically important nodes in a network.

Another well-known measure in the literature is the Aggregate Vulnerability index (AV) developed by Greenwood et al. (2015), which estimates the fraction of system equity capital lost due to fire-sales spillovers in a stress

scenario under the assumption that financial intermediaries seek to maintain constant leverage. This indicator aims to assess the degree of aggregate vulnerability in the system due to fire sales of a large set of firms. The index is additive and so can be decomposed into each bank’s contribution to fire sales. The systemic importance of bank  $i$  is then bank  $i$ ’s contribution to AV. In an extension, [Duarte and Eisenbach \(2021\)](#) decompose the index into various determinants such as the size of the system relative to the wealth of outside buyers, leverage, the average leverage adjustment speed, and illiquidity concentration. Both decompositions are convenient as they allow us to link both the micro and macroprudential dimensions, providing supervisors with information on the sources of aggregate vulnerability. Moreover, the methodology permits to perform counterfactual exercises by modifying specific banks’ balance-sheet components so as to test results under alternative scenarios such as lower capital and liquidity requirements. [Aldasoro et al. \(2022\)](#) integrate the AV measure into an accounting-based stress-testing framework to assess loss dynamics in the banking sector where both direct interbank exposures and indirect exposures due to overlapping portfolios are present. This allows for a comparison between the size of AV depending on which contagion channels are allowed to play out. In related work, [Cont and Schaanning \(2017\)](#) develop an indicator for assessing indirect price-mediated contagion via fire sales, which they call the Indirect Contagion Index. The indirect contagion index shows a strong and positive relationship with fire sales losses, thereby providing an easy way to compute the IC index directly from portfolio holdings data.

Contrary to [Duarte and Eisenbach \(2021\)](#), [Greenwood et al. \(2015\)](#), and [Cont and Schaanning \(2017\)](#) in which the model outputs are a function of an exogenous macro shock affecting the price of the securities, [Covi et al. \(2021\)](#) measures contagion potential in the system given an exogenous bank default. Extending this, [Covi et al. \(2022\)](#) develop Capital at Risk (CaR) and Conditional Capital at Risk (CCaR) indicators, which quantify respectively banks’ 1-year ahead expected and tail losses conditional to current economic and financial conditions. These indicators may help to monitor cyclical and structural developments in banks’ solvency position as a function of quarterly changes in banks’ portfolios of exposures, counterparty default probabilities, loss given default parameters, and a correlation structure of counterparty defaults. Regulators may use these measures to rank banks by their vulnerability scores and contagion potential so as to identify tipping points in the network that may lead to cascade effects. These indicators may be further decomposed according to country and sectoral contributions, risk channels, as well by the amount of losses experienced during first and second round effects (amplification mechanisms). This decomposition is useful especially for identifying the sources of potential contagion and vulnerability for monitoring purposes.

Turning to funding liquidity risk, [Cont et al. \(2020\)](#) develop a structural framework for the joint stress testing of solvency and liquidity. The authors derive the concept of ‘Liquidity at Risk’, which quantifies the liquidity resources required for a financial institution facing a stress scenario. The output is a function of external shocks to solvency and endogenous liquidity shocks arising from these solvency shocks. The liquidity at risk indicator is a forward-looking measure of liquidity stress conditional on a scenario defined in terms of co-movements in risk factors. The net liquidity outflow is function of funding flows such as maturing liabilities, net scheduled outflows, net outflow of variation margin, credit-contingent cash outflows. In this respect, the liquidity shortfall is given by the difference between the Liquidity at Risk measure and the liquid assets available. In contrast to the Liquidity Coverage Ratio (LCR), which is estimated based on historical data on margin calls or average runoff rates, Liquidity at Risk is a portfolio-specific and forward-looking concept.

As we have seen, most of the studies in the literature have developed entity-specific indicators of contagion and vulnerability which may be used for microprudential supervision. Macroprudential indicators measuring the level of systemic risk in the system seem to be less common. This may reflect the lack of a definition of systemic risk and the choice of the triggering event (exogenous macro scenario / exogenous bank default) used to calculate the output measures. One exception is [Covi et al. \(2020\)](#) who construct a modelling framework in order to derive a probabilistic measure of systemic risk. The authors model stochastically banks’ credit risk losses stemming from correlated corporate defaults in the real economy and augment them via financial contagion channels at play in the interbank network. Hence, the systemic risk measure is defined as the probability of a systemic event occurring, which they define as an event in which 1.5 per cent of all banks in the system enter into distress or default within the same time period. The ratio between the number of systemic events and the overall number of simulations/scenarios is their final output measure. The outputs of the model also decompose and quantify the sources of systemic risk into correlated economic shocks, and financial contagion such as credit, liquidity and market risks. Furthermore, the authors compute entity-specific default probabilities (microprudential perspective) and the average default probability in the system (macro perspective). These output measures are especially useful for monitoring the build-up of systemic risk in the system. The framework may be also useful to perform counterfactual policy exercises by changing various components of the system so as to assess the benefits of specific prudential policies to curb systemic externalities.

## 6.2 Prudential Tools

Outputs from system-wide stress testing models can be used to inform a wide-range of policy questions, such as: (a) how to identify key players in the financial system such as entities that are too-big too-fail or too-

Model-based Indicators	Risk Type	Indicator	Source	Perspective
Solvency	Credit Risk	DebtRank; Feedback Centrality	Battiston et al. (2012)	Micro
Solvency	Fire-Sales	Aggregate Vulnerability	Greenwood et al. (2015); Duarte and Eisenbach (2021); Aldasoro et al. (2022)	Micro and Macro
Solvency and Liquidity	Fire-sales	Indirect Contagion Index	Cont and Schaanning (2017)	Micro
Solvency	Credit Risk and Market Risk	Contagion and Vulnerability Indexes; Capital at Risk and Conditional Capital at Risk Indicators	Covi et al. (2022); Covi et al. (2021); Espinosa-Vega and Solé (2011)	Micro and Macro
Liquidity	Funding Risk	Liquidity at Risk	Cont et al. (2020)	Micro
Solvency and Liquidity	Credit Risk and Fire-sales	Systemic Risk Probability; Average Bank Default Probability	Covi et al. (2020)	Macro

Table 13: Model-based Indicators

central-too-fail; (b) how to monitor the build-up of idiosyncratic and systemic risk; (c) how to disentangle the channels of risk transmission and amplification; and (d) how to assess the costs and benefits of prudential requirements. The key and appealing feature of these frameworks is that regulatory requirements represent the device triggering model dynamics. When a constraint in the model binds, agents seek to improve their solvency, liquidity or leverage, and this in turn may trigger contagion and market dynamics. Given this, researchers have explored how these models can be used as a policy laboratory to test and calibrate the introduction of new prudential regulations – we summarise this literature in Table 14. However, as the decision rules in these models are typically not grounded in microeconomic theory, such exercises are subject to the Lucas Critique.

Starting with liquidity regulation, Aldasoro and Faia (2016) evaluate the extent to which liquidity regulations are able to contain contagion and systemic risk. The authors test the effects of a phase-in of the Liquidity Coverage Ratio (LCR) and find that, while this measure can reduce systemic risk in the initial phase, it might also increase systemic risk in the final phase as a high LCR reduces the insurance function of interbank markets. Moreover, they also find that when the LCR is applied equally to all banks, it imposes unnecessary liquidity shortages on banks that are mildly leveraged and which would otherwise act as interbank liquidity providers. The authors suggest that setting LCR requirements differentially across banks according to their systemic importance is more effective in delivering a stable system. Aldasoro et al. (2017) expand on this analysis to explore the stability/efficiency trade-off. The authors find that liquidity requirements – modelled as the fraction of cash over deposits – unequivocally decrease systemic risk, but at the cost of lower efficiency in terms of aggregate investment in illiquid assets. On the other hand, equity requirements modelled as the ratio of equity at market prices (at the numerator) over risk weighted assets (at the denominator) also tend to reduce risk (hence increase stability), though without reducing overall investment. The authors conclude that the results provide general support for the Basel III approach based on complementary regulatory metrics.

Similarly Gai et al. (2011) study funding contagion in the interbank market. The authors discuss how a range of policy measures such as tougher liquidity regulation, macroprudential policy, and surcharges for systemically important financial institutions could make the financial system more resilient. They find that an increase in the amount of liquidity assets in the system (from 2 to 3 percent) makes the interbank market less prone to collapse. Moreover, consistently with the findings of Aldasoro and Faia (2016), the authors suggest that targeted liquidity requirements – higher for those banks identified as highly contagious while smaller for those peripheral in the network – are more effective than homogeneous liquidity requirements. In this respect, to reduce the negative contagion effects of bank runs the authors suggest a liquidity rule which is a positive function of each bank’s total interbank assets, calibrated around 10 percent. The authors also provide evidence on the effectiveness of introducing haircut-dependent (time-varying) liquidity requirements since haircuts tend to decrease during the upswing of a cycle as the financial system becomes increasingly exuberant. Overall, empirical evidence and counterfactual policy exercises support the effectiveness of a set of complementary micro and macro prudential measures targeting respectively specific junctures of the network as well as the system’s aggregate requirements.

Gorpe et al. (2019) study the effects of contagion in the euro area interbank network by modelling banks’ behavioural responses to solvency distress and default conditions. The former is defined as a breach of a bank’s capital buffer requirements, while the latter as a breach of minimum capital requirements. The authors calibrate

and measure the effectiveness in mitigating contagion spillovers by applying a capital surcharge in the form of either minima, buffer requirements or a combination of both. Overall, the approach finds that an increase in capital buffer requirements tends to be more effective than an increase in the minimum capital requirements since the former decreases the average number of banks' defaults and the average amount of losses induced to the system more than in the latter case. Nevertheless, the likelihood of experiencing distress events increases. The model has been calibrated to the euro area interbank network covering 2,800 consolidated banking groups worldwide. Similarly, [Farmer et al. \(2020\)](#) calibrate the size of regulatory buffer requirements using a system-wide financial stress testing methodology for the European financial system. The authors find that the size of capital buffers needed to limit systemic risk could be severely underestimated if calibrated ignoring system-wide feedbacks. Furthermore, increasing regulatory buffers tends to bring down contagion defaults more than initial defaults thereby highlighting the role played by regulatory capital buffers in containing contagion and in reducing the inherent shock amplifying tendency of the financial system. Overall, the authors conclude that relying solely on microprudential stress tests to calibrate buffer requirements may lead to overestimating banks' resilience.

Another interesting application from the perspective of a resolution authority is the work made by [Hüser et al. \(2018\)](#) in the context of assessing the systemic implications of the newly-introduced 'Bail-in tool'. The approach is suitable to measure the level of contagion spillovers in the interbank network conditional to the seniority structure of bail-inable bilateral interbank contacts. This methodology provides insights on the systemic impact that the interbank network may undergo given a bank entering into resolution and on the effectiveness of TLAC-MREL regulations ([FSB, 2019](#)). Although the cross-holdings of liabilities is limited in the euro area interbank network, authors find that shareholders and subordinated creditors are always affected by the bail-in, while senior unsecured creditors are affected in 75 percentage of the cases. Hence, the approach can be also used as a resolution-regulatory tool to calibrate ad-hoc instrument-exemptions and institutions-specific levels of bail-inable liabilities.

Overall, there is substantial promise in the use of macroprudential stress testing models to inform the design and calibration of prudential rules. These models seek to capture complex dynamic interactions and feedback effects, the impact of which is likely to be critical for informing optimal policy. The literature to date has found efficiency benefits to differentiating the calibration of liquidity and capital requirements according to the systemic importance of financial institutions in the network. A practical question for future research is to assess whether we can design allocation rules that are likely to be robust across a wide variety of modelling frameworks, taking into account uncertainty over behaviour under stress. In addition, we see significant value in researchers expanding efforts to apply macroprudential stress test models to explore more complex frontier policy issues such as the optimal combination of capital and liquidity requirements in the banking system, and – more blue-sky still – the costs and benefits of applying prudential capital or liquidity requirements to entities in the non-bank financial system. Although it may be some time before insights from such models are ready to inform policy choices.

<b>Prudential Tools</b>	<b>Measure</b>	<b>Exercise</b>	<b>Source</b>	<b>Perspective</b>
<b>Liquidity</b>	LCR	Calibration	<a href="#">Aldasoro and Faia (2016)</a>	Micro
<b>Liquidity and Solvency</b>	LCR liquidity and equity requirements	Cost-Benefit Analysis	<a href="#">Aldasoro et al. (2017)</a>	Micro
<b>Liquidity</b>	Liquid Assets Haircuts	Calibration	<a href="#">Gai et al. (2011); Aldasoro et al. (2017)</a>	Micro and Macro
<b>Solvency</b>	Minimum capital requirements Capital Buffer Requirements	Calibration	<a href="#">Gorpe et al. (2019)</a>	Micro
<b>Solvency</b>	Buffer requirements	Calibration	<a href="#">Farmer et al. (2020)</a>	Micro
<b>Solvency</b>	Bail-in Mechanism	Calibration	<a href="#">Hüser et al. (2018)</a>	Micro
<b>Solvency</b>	Countercyclical Capital Buffer	Calibration	<a href="#">BoE (2016); FED (2016); O'Brien et al. (2018); Bennani et al. (2017); Van Oordt (2022);</a>	Macro

Table 14: Prudential Tools

## 7 Concluding lessons from this survey

In this final section of the paper, we draw out some take-away lessons from this survey. We first discuss lessons for financial stability policymakers, where the emphasis is on emerging insights from this literature that can inform the design of supervisory stress tests. We then discuss lessons for researchers involved in developing macroprudential stress testing models, where our emphasis is prioritising addressing gaps in this literature that impede the utility of these models for informing policy.

### 7.1 Lessons for policymakers and for the design of supervisory stress tests

The current generation of supervisory stress testing frameworks used by regulators to assess banking system resilience (e.g. the Federal Reserve’s CCAR, the Bank of England’s Annual Cyclical Scenario (ACS), and the EBA stress test) is mainly focused on quantifying the direct losses that may arise under stress from credit, market, operational and litigation risks. As we have showcased in the present survey, one undoubted success of the macroprudential stress testing literature in recent years is the progress it has made in identifying and modelling a range of non-linear propagation channels that can amplify the effects of shocks hitting an individual bank or set of banks, leading to losses spreading across the financial system. These channels centre around contagion mechanisms operating via solvency risk (including channels that take effect prior to default via credit valuation adjustments), market liquidity risk, and funding liquidity risk. Policymakers are cognisant that there is still work to be done to incorporate such channels into supervisory stress tests (see e.g., [Tarullo \(2016\)](#)). Examples of progress include the 2017 Bank of England ACS, where three feedback models have been applied to the results: a solvency contagion model,<sup>22</sup> a wholesale funding cost model,<sup>23</sup> and a fire sales model<sup>24</sup> as well as the Bank of England’s 2023 system-wide exploratory scenario that will investigate the behaviours of banks and non-bank financial institutions following a shock, as well as their potential for shock amplification.

The literature has made progress too in uncovering the factors that determine the significance of these amplification channels. For a given-sized shock hitting the system, its eventual impact will depend on (a) the size of financial institutions’ capital and liquidity buffers, (b) the liquidation strategies financial institutions adopt when they need to raise cash, and (c) the topology of the financial network. We discuss each in turn.

With respect to financial institutions’ buffers of capital and liquidity, a robust insight from the models we survey is the importance of buffers being usable. Buffer usability has a precise definition in these models: it is the quality that allows losses or funding withdrawals to be absorbed without triggering asset sales, liquidity hoarding or a tightening of credit conditions - that is, a usable buffer allows shocks to be absorbed rather than amplified and spread to others in the network. The papers we survey generate starkly different results depending on whether existing capital and liquidity buffers are assumed to be usable in this sense. This is nowhere clearer than in the case in models of fire sale contagion. There is a surprisingly high variance in the magnitude of impacts reported by papers analysing this channel - a variance that can be explained substantially by differing implicit assumptions about buffer usability. Papers that assume banks attempt to maintain their leverage ratios following shocks and hence do not view their capital buffers as usable find significantly larger effects from shocks hitting the system. This observation chimes with the attention paid to buffer usability by regulators internationally.<sup>25</sup>

Another insight from the recent stress testing literature that focuses on stress dynamics in the investment fund sector is that the selling behaviour funds adopt to raise cash to pay redeeming investors can matter significantly for the scale of fire sale losses generated for the system. In particular, when funds raise cash to pay redeeming investors by selling their most liquid assets first, the impact on asset prices is normally significantly smaller than when funds instead sell a ‘vertical slice’ of their assets under management. This can mute the feedback loop between fund redemptions and asset prices declines. That said, a ‘liquid assets first’ policy might be expected to heighten investors’ incentives to redeem to avoid being left with a less liquid pool of assets. This is an example of a more general trade-off that can occur in macroprudential stress testing models between micro-prudential and investor protection consideration on the one hand, and macro-prudential and systemic stability considerations on the other. Vertical slicing avoids favouring redeeming investors at the expense of those who remain, but as it involves sales of illiquid assets, it opens the possibility of greater spillovers to others with asset holdings in common.

A related insight from the recent literature is that the vulnerability of the system to fire sale losses might depend upon which of the various post-GFC regulatory constraints we impose on financial institutions is the binding one. To take a simple example, consider the optimal liquidation strategy of a bank facing a binding

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<sup>22</sup>The model examines how deteriorating capital positions lead to revaluation of interbank debt claims, which in turn can affect banks’ capital positions further and is based on [Bardoscia et al. \(2019\)](#)

<sup>23</sup>The model maps changes in banks’ leverage ratios to increases in wholesale funding costs and is based on [Dent et al. \(2017\)](#)

<sup>24</sup>The Bank of England has adapted the methodology developed by [Cont and Schaanning \(2017\)](#), which seeks to quantify a) the impact of the sales of traded securities on the prices of those securities, and b) the realised and mark-to-market losses that result from asset sales.

<sup>25</sup>See eg the work of the Basel Committee in this area, summarised by [de Cos \(2021\)](#).

risk-based capital constraint with one facing a binding leverage constraint. The optimal strategy will trade-off at the margin any liquidation losses suffered against the impact in alleviating the constraint. Intriguingly, it follows that a binding risk-based capital constraint may generate stronger incentives to sell illiquid risky assets first to the extent they have higher risk weights, implying larger spillovers to the system compared to the case where leverage binds.

With respect to the topology of the network, this is an area where there appear to be no straightforward take-away policy implications. It has long been appreciated that systemic risk is likely to be a non-linear function of network structure (see for example discussion on this in Hüser (2015)), with fragility highest in networks where connectedness is either very low, implying little diversification, or very high, implying a greater potential for distant shocks to spread throughout the system. Despite this, there has been little attention to the influence of network structure in driving results from stress testing models.

## 7.2 Lessons for researchers developing macroprudential stress testing models

The models we have surveyed in this paper have made great strides in recent years in capturing new propagation channels and more sophisticated behaviour by financial institutions under stress. Substantial progress has been made too in grounding stress testing models in empirical balance sheet data of network interconnections, allowing for a more realistic assessment of systemic risk than that possible in the earlier generation of models that relied on estimates of such exposures.

Despite these advances, there remains substantial work to be done to bring these models to the point where they can inform macroprudential policy decisions. We highlight three (highly ambitious) directions where the returns to further research seem to us to be particularly high. Our suggestions are informed by recent stress episodes, most importantly the period of severe stress in the financial system that struck when the extent of the spread of COVID-19 became apparent in March 2020.<sup>26</sup> What features of stress testing models would have been particularly informative and useful during this period?

First, more attention needs to be devoted to understanding the potential for amplification in sectors of the non-bank financial system during periods of stress. This sector has grown rapidly as a source of credit provision to the real economy over the past decade, and it was the epicentre of stress during the March 2020 ‘dash for cash’ crisis. There has been good progress in adapting models originally designed to study fire sale risk in the banking system to the asset management sector. Despite recent progress, it remains relatively understudied in the stress testing literature. Amongst the priority issues this literature could be developed to address are questions such as:

- Under what conditions can asset managers contribute materially to systemic stress via the feedback loops between redemptions, asset sales and asset prices?
- What drives the behaviour of insurance companies and pension funds in a stress and under what conditions do they stabilise markets versus exacerbate their stress?
- How resilient are central counterparties to a period of pronounced market stress and what is the most efficient way of reducing procyclicality in their margin requirements?
- What influences the capacity of market intermediaries such as broker dealers to provide liquidity in periods of stress, and where regulatory constraints (e.g., the leverage ratio) impinge on this capacity, is there scope to redesign these constraints without impairing resilience?

Researchers will require more granular and high-frequency data on fund flows, asset holdings and leverage to support this effort.

Second, the ‘dash for cash’ episode of March 2020 highlights the importance of analysing interconnectedness across the system as a whole. Many of the fault-lines that were highlighted by this crisis cannot be adequately analysed without taking a wide lens view of how sectors interact to propagate stress. Firms in this diverse landscape interact in complex funding chains, which recycle liquidity and collateral across the system with the aim of improving efficiency. Via this process, sectors become interconnected and vulnerable to liquidity shocks, the effects of which can ripple through the system via redemptions, margin calls, tighter financial conditions in repo markets, and asset fire sales.<sup>27</sup>

While the scale of the research challenge involved in building multi-sectoral models of the non-bank financial system is clearly substantial - not least given the international nature of the markets in question - models of this system are essential if we are to analyse the behaviour of the overall demand and supply of liquidity under stress.

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<sup>26</sup>See for an overview on banks Li et al. (2020), Giese and Haldane (2020) and Schimpf et al. (2020), for non-banks Eren et al. (2020) and Czech et al. (2021), for CCPs Huang and Takáts (2020) and for a system-wide view Hüser et al. (2021).

<sup>27</sup>See Kashyap (2020) for a discussion of the ‘liquidity multiplier’ created by the system of market-based finance.



Third, it has been clear since the Global Financial Crisis that we require stress testing models that incorporate comprehensive two-way interactions between the financial system and the real economy - that is, models that permit an examination of banks' reactions to stress scenarios, the knock-on implications of those reactions for credit supply and the level of economic activity, and the resulting impacts on asset performance. This would involve integrating macroprudential stress testing models with the now quite mature literature on macroeconomic models with financial frictions (e.g., [Gertler and Kiyotaki \(2015\)](#)).

Such macro-financial feedbacks have been central to macroprudential policymakers' thinking since the COVID-19 pandemic began. In the absence of suitable existing models, policy choices had to rely on stylised assumptions and ad hoc models created at short order. In addition to providing better grounded estimates of such channels, stress testing models with macro-feedbacks would also offer the promise of allowing researchers to examine systematically the macroeconomic implications of liquidity dry-ups and policy options designed to remedy such problems.

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