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Models of Financial Stability and Their Application in Stress Tests

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DRAFT - Comments Welcome
Review Chapter for:
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Abstract

This paper reviews the literature on heterogeneous agent models of financial stability and their application in stress tests. We open with the observation that the financial system is a complex system, which heterogeneous agent models are well-suited to analyze. The paper then proceeds in two parts. In the first part, we discuss the fundamental drivers of systemic risk in financial systems, and set out how our understanding of them can be informed by heterogeneous agent models. We focus on models of systemic risk resulting from leverage constraints and models of financial contagion due to interconnectedness. In the second part of this review, we discuss how the conceptual insights from leverage and contagion models can be combined to model and understand systemic risk more broadly and to build robust and data-driven stress tests.

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1 Introduction

The financial system is a classic example of a complex system. It consists of many diverse actors, including banks, mutual funds, hedge funds, insurance companies, pension funds and shadow banks. All of them interact with each other, as well as interacting directly with the real economy (which is undeniably a complex system in and of itself). The financial crisis of 2008 provided a perfect example of an emergent phenomenon. While the causes of the crisis remain controversial[1], a standard view goes like this: A financial market innovation called mortgage-backed securities made lenders feel more secure, allowing them both to extend more credit to households, and to purchase large quantities of securities on credit. Liberalized lending fueled a housing bubble; when it crashed, the fact that the portfolios of most major financial institutions had significant holdings of mortgage backed securities caused large losses. This is turn caused a credit freeze, cutting off funding for important activities in the real economy, and generating a global recession that cost the world an amount that has been estimated to be as high as fifty trillion dollars, the order of half a year of global GDP. The crisis has made everyone aware of the complex nature of the interactions and feedback loops in the economy, and has driven an explosive amount of research attempting to better understand the financial system from a systemic point of view. It has also underlined the policy relevance of the complex systems approach.

The financial system is sufficiently complicated that it is not yet possible to model it realistically. Existing models only attempt a stylized view, trying to elucidate the underlying mechanisms driving financial stability. There are currently two basic approaches. The mainstream approach has been to focus on situations where it is possible to compute an equilibrium. The computational difficulty of such models generally requires making very strong simplifications, e.g. studying only a few actors and interactions at a time. This has been useful to elucidate some of the key mechanisms, driving financial instabilities and financial contagion, but it comes at the expense of simplifications that limit the realism of the conclusions. There is also a concern that, particularly during a crisis, the assumptions of rationality and equilibrium are too strong.

The alternative approach abandons equilibrium and rationality and replaces them with stylized behavioral assumptions. This approach often relies on simulation. This has the advantage that it becomes easier to study more complicated situations, e.g. with more actors and more realistic institutional constraints. It also potentially makes it possible to study multiple channels of interaction; even though so far very little has been done, it is clear that this plays an important role. The disadvantage is that the assumptions about behavior may be ad hoc, and even when they are well supported on empirical grounds, they may be context dependent (such models typically fail the Lucas critique).

This review will focus primarily on the computational approach, though we will attempt to discuss key influences and interactions with the more traditional equilibrium approach. We

[1] Indeed we will mention some alternative views here.

believe that the computational approach will become increasingly important with time, for several reasons. One is that this approach is easier to bring to the data, and data is becoming more readily available. Many central banks are beginning to collect comprehensive data sets that make it possible to monitor the key parts of the financial system. This makes it easier to test the realism of behavorial assumptions, making such models less ad hoc. With such models it is potentially feasible to match the models to the data in a literal, one-to-one manner. This has not yet been done, but it is on the horizon, and if successful such models may become valuable tools for assessing and monitoring financial stability, and for policy testing. In addition, computational power is always improving. This is a new area of pursuit and the computational techniques and software are rapidly improving.

The actors in the financial system are highly interconnected, and as a consequence network dynamics plays a key role in determining financial stability. The distress of one institution can propagate to other institutions, a process that is often called *contagion*, based on the analogy to disease. There are multiple channels of contagion, including counterparty risk, funding risk, and common assets. *Counterparty risk* is caused by the web of bilateral contracts, which make one institutions assets another's liabilities. When a borrower is unable to pay, the lender's balance sheet is affected, and the resulting problems may in turn be transmitted to other parties. If a lender comes under stress, this may create problems for borrowers because loans fail to be extended in the future. Institutions are also connected in many indirect ways, e.g. by common asset holdings, also called overlapping portfolios. If an institution comes under stress and sells assets, this depresses prices, which can cause further selling, etc. And there are of course other channels of contagion, such as common information, that can affect expectations and interact with the more mechanical channels described above.

These channels of contagion cause nonlinear interactions that can create positive feedback loops, that can amplify external shocks or even generate purely endogenous dynamics, such as booms and busts. Nonlinear feedback loops can also be amplified by behavioral and institutional constraints and by bounded rationality (often in the context of incomplete information and learning)

Behavioral and institutional constraints force agents to take actions that they would prefer to avoid in the absence of the constraint. Often such behavioral constraints are imposed by a regulator but they can also result from bilateral contracts between private institutions. In principle, regulatory constraints, such as capital or liquidity coverage ratios, are designed to increase financial stability. In many cases however, these constraints focus on increasing the resilience of a financial institution to idiosyncratic shocks rather than the system as a whole. Take the example of a leverage constraint. If a financial institution has high leverage, a small shock may be enough to push it into insolvency. Hence, from a regulatory perspective, a cap on leverage seems like a good idea. However, as we will discuss below, a leverage constraint may have the adverse side effect that it forces distressed institutions to sell into falling asset markets. Such distressed selling may lead to a further fall in prices. Of course leverage constraints are needed, but the point is that their effects can go far beyond the failure of individual institutions, and the way in which they are enforced can make a big difference. Similar positive feedback results from other behavioral constraints as well.

This brings up the distinction between *microprudential regulation*, which is designed to benefit individual institutions without considering the effect on the system as a whole, vs. *macroprudential regulation*, which is designed to take systemic effects into account. These can come into dramatic conflict. For example, we will discuss the base of Basel II, which provided perfectly sensible rules for risk management from a microprudential point of view, but which likely caused substantial systemic risk from a macroprudential point of view, and indeed may have been a major driver of the crisis. It is ironic that prudent behavior of an individual can cause such significant problems for society as a whole.

Rational agents with complete information might be able to navigate the risks inherent to the financial system. Indeed, optimal behavior might well mitigate the positive feedback resulting from interconnectedness and behavioral constraints. However, we believe that optimal behavior in the financial system is rare. Instead, agents are restricted by bounded rationality. Their limited understanding of the system in which they operate forces agents to rely on simple rules as well as biased methods to learn about the state of the system and form expectations about its future states. Suboptimal decisions and biased expectations exacerbate the destabilizing effects of interconnectedness and behavioral constraints but can also lead to financial instability on their own.

In the following sections we will first discuss the fundamental drivers of systemic risk outlined above in more detail and how our understanding of them can be informed by heterogeneous agent models. In particular, we will focus on models of systemic risk resulting from leverage constraints and models of financial contagion due to interconnectedness. In the second part of this review we will discuss how the conceptual insights from leverage and contagion models can be combined to build robust and data driven systemic stress tests.

2 Two approaches to modeling systemic risk

As mentioned in the introduction, traditionally finance has focused on modeling systemic risk in highly stylized models that are analytically tractable. These efforts have improved our understanding of a wide range of phenomena related to systemic risk ranging from bank runs (Diamond and Dybvig (1983), Morris and Shin (2001)), credit cycles (Kiyotaki and Moore (1997), Brunnermeier and Sannikov (2014)), balance sheet (Allen and Gale (2000)) and information contagion (Acharya and Yorulmazer (2008)) over fire sales (Shleifer and Vishny (1992)) to the feedback between market and funding liquidity (Brunnermeier and Pedersen (2009)). A comprehensive review that does justice to this literature is well beyond the scope of this paper. However, we would like to make a few observations with regards to this traditional modeling approach and contrast it with the heterogeneous agent approach.

Traditional models place great emphasis on the incentives and information structure of agents in a financial market. Given those, agents behave strategically taking into account their beliefs about the state of the world and other agents strategies. The objects of interest are then the game theoretic equilibria of this interaction. This allows studying the effects of, among others, asymmetric information, uncertainty or moral hazard on the stability of the financial system. While these models provide valuable qualitative insights, they are typically only tractable in very stylized settings. In particular, models are usually restricted to a small number or a continuum of agents, a few time periods and a drastically simplified institutional and market set up. This can make it difficult to draw quantitative conclusions from such models.

Heterogeneous agent models typically place less emphasis on incentives and information and instead focus on how the dynamic interactions of behaviorally simple agents can lead to complex aggregate phenomena, such as financial crises, and how outcomes are shaped by the structure of this interaction and the heterogeneity of agents. From this perspective, the key drivers of systemic risk are the amplification of dynamic instabilities and contagion processes in financial markets. Complicated strategic interactions and incentives are often ignored in favor of simple, empirically motivated behavioral rules and a more realistic institutional and market set up. Since these models can easily be simulated numerically, they can in principle be scaled to a large number of agents and, if appropriately calibrated, can yield quantitative insights.

Two common criticisms leveled against heterogeneous agent models are the lack of strategic interactions and the reliance on computer simulations. The first criticism is fair and, in many cases, highlights an important shortcoming of this approach. Hard wired behavioral rules need to be carefully calibrated against real data, and even when they are, they can fail in new situations where the behavior of agents may change. For computer simulations to be credible their parameters need to be calibrated and the sensitivity of outcomes to those parameters needs to be understood. The latter in particular is more challenging in computational models than in tractable analytical models.[2]

Traditional and heterogeneous agent models are complements rather than substitutes. Some heterogeneous agent models use myopic optimisation, and in the future the line between the two may become increasingly blurred.[3] As methods such as computational game theory or multi-agent reinforcement learning mature, it may become possible to increasingly introduce strategic interactions into computational heterogeneous agent models. Furthermore, as computational resources and large volumes of data on the financial system become more accessible, parameter exploration and calibration should become increasingly feasible. Therefore, we are optimistic that, provided technology progresses as expected,[4] in the future heterogeneous agent models will be able to overcome some of the shortcomings discussed above. And as we demonstrate here, they have already led to important new results in this field, that were not obtainable via analytic methods.

[2] In our view, what is not fair is to regard computer situations as inherently inferior to analytic results. Of course, all else equal, analytic models are preferable because the ease of varying parameters leads to a deeper understanding with less effort. But many aspects of the economic world are not simple, and in most realistic situations computer simulations are the only possibility. Good practice is to make code freely available and well documented, so that results are easily reproducible.

[3] In fact this is already the case in the literature on financial and economic networks.

[4] It seems unlikely that scientists' ability to analytically solve models will improve as quickly as numerical techniques and heterogeneous agent simulations, which have Moore's law on their side.

We will further explore this vision towards the end of this review. The following sections will be dedicated to our current understanding of dynamic instabilities resulting from leverage constraints and how different contagion channels on financial networks can lead to a propagation of the stress through a financial system. We first focus on the potentially destabilizing effects of leverage as they form the basis of fire sale models discussed in the contagion section and because they are thought to have contributed to the build up of risk prior to the great financial crises. We then proceed to contagion models as they form the scientific bedrock of advanced stress testing models that will be discussed in the second part of this review. Naturally, we will not be able to provide a complete overview of the heterogeneous agent model literature devoted to various aspects of financial stability. For example, important topics that we will not be able to discuss include the role of heterogeneous expectations or time scales in the dynamics of financial markets, see for example Brock and Hommes (1998), LeBaron (2012).

3 Leverage and Endogenous Dynamics in a Financial System

3.1 Leverage and balance sheet mechanics

Many financial institutions borrow and invest the borrowed funds into risky assets. Suppose an investor has equity E and borrows an amount D such that its total assets are $A = E + D$. The investor's leverage is the ratio of assets to equity $\lambda = A/E$. Three simple properties of leverage are worth noting at this point. First, ceteris paribus, leverage determines the size of the investor's balance sheet. Second, leverage boosts asset returns and third, leverage increases when the investor incurs losses, again ceteris paribus. Below, we discuss each property in turn.

Clearly, for a fixed amount of equity, an investor can increase the size of its balance sheet by increasing its leverage. Further, it is easy to show that, if r_t is the asset return, the equity return is $u_t = \lambda r_t$. In good times, leverage allows an investor to boost its return. In bad times however, even small negative asset returns can drive the investor into bankruptcy provided leverage is sufficiently high. Given the potential risks associated with high leverage, an investor typically faces a leverage limit which may be imposed by a regulator, as is the case for banks, or by creditors via a haircut on collateralized debt.

Finally, why does leverage increase when the investor incurs losses? From the definition of leverage it can be seen that $\lambda > 1$ implies $\partial\lambda/\partial p < 0$. In other words, whenever an investor is leveraged ($\lambda > 1$), a decrease (increase) in asset prices leads to an increase (decrease) in its leverage.

In what follows we discuss how these three properties of leverage, in combination with reasonable assumptions about investor behavior, can lead to financial instability. We begin by discussing how leverage constraints can force investors to sell into falling markets even if they would prefer to buy in the absence of leverage constraints. We then show how a leverage constraint based on a backward looking estimator of market risk can lead to endogenous volatility and leverage cycles.

3.2 Leverage constraints and margin calls

Consider again the simple investor discussed above. Suppose the investor faces a leverage constraint $\overline{\lambda}$ and has leverage $\lambda_{t-1} < \overline{\lambda}$.[5] The investor has to decide on an action at time $t-1$ to ensure that he does not violate its leverage constraint at time t. Suppose the investor expects the price of the risky asset to drop sufficiently from one period to the next, such that its leverage is pushed beyond its limit, i.e. $\lambda_t > \overline{\lambda}$. In this situation the investor has two options to decrease its leverage: raise equity or sell part of its assets (or some combination of the two of course). Raising equity can be time consuming or even impossible during a financial crisis. Therefore, if the leverage constraint has to be satisfied quickly or if new equity is not available, the investor has to sell at least $\Delta A_{t-1} = \max\{0, (\mathbb{E}_{t-1}[\lambda_t] - \overline{\lambda})\, \mathbb{E}_{t-1}[E_t]\}$ of its assets to satisfy its leverage constraint, where $\mathbb{E}_t[\cdot]$ is the conditional expectation at time t. In the following we will set $\mathbb{E}_t[\lambda_{t+1}] = \lambda_t$ and $\mathbb{E}_t[E_{t+1}] = E_t$. This can be done for simplicity or because a contract forces the investor to make adjustments based on current rather than expected values. In this case we have simply $\Delta A_t = \max\{0, (\lambda_t - \overline{\lambda})E_t\}$.

If λ_t exceeds the leverage limit due to a drop in prices, the investor will sell into falling markets. This may lead to a further drop in prices if the investor's selling has an impact on prices. These are the ingredients for the following feedback loop: The investor's leverage is pushed beyond its constraint by a fall in the price of the risky asset upon which the investor sells part of its assets to satisfy its leverage constraint. In doing so the investor causes a further drop in prices. This may again push its leverage beyond its constraint. This results in an amplification of the initial drop in asset prices.

This simple mechanism has been discussed by a number of authors, see for example Gennotte and Leland (1990), Geanakoplos (2010), Thurner et al. (2012) or Shleifer and Vishny (1997), Gromb and Vayanos (2002), Fostel and Geanakoplos (2008). Thurner et al. (2012) incorporate this mechanism in a heterogeneous agent model of leverage constrained value investors. In the remainder of this section we will introduce their model and discuss some of the quantitative results they obtain for the effect of leverage constraints on asset returns.

There is a set $\mathcal{V}$ of funds, a representative noise trader and a representative "fund investor" that allocates capital to the funds. There is an asset of supply N with fundamental value V that is traded by the funds and the noise trader at discrete points in time $t \in \mathbb{N}$. Every period a fund i takes a long position $A_{it} = \lambda_{it} E_{it}$ provided its equity satisfies $E_{it} \geq 0$. The fund's leverage is given by the heuristic

$$\lambda_{it} = \min\{\beta_i m_t \ , \ \overline{\lambda}\},$$

where $m_t = \max\{0, V - p_t\}$ is the mispricing signal and β_i is the fund's aggressiveness. In other words, the fund goes long in the asset if the asset is underpriced relative to its fundamental value V. The noise trader's long position follows a transformed AR(1) process. The price of the asset is determined by market clearing. Every period, the fund investor adjusts its capital

[5] As mentioned above a leverage constraint can be the result of regulation or contractual obligations.

allocation to the funds, withdrawing capital from poorly performing funds and investing into successful funds relative to an exogenous benchmark return.

Before considering the dynamics of the full model, let us briefly discuss the limit where the funds are small, i.e. $E_{it} \to 0$. In this case, in the absence of any significant effect of the funds, log price returns will be approximately iid normal due to the action of the noise trader. This serves as a benchmark. The authors then calibrate the parameters of the model such that funds are significant in size and prices may deviate substantially from fundamentals. This corresponds to a regime where arbitrage is limited as in Shleifer and Vishny (1997). The authors also assume that funds differ substantially in their aggressiveness β_i but share the same leverage constraint $\overline{\lambda}$ and initial equity E_{i0}.

In this setting the funds' leverage and wealth dynamics can lead to a number of interesting phenomena. When the noise trader's demand drives the price below the asset's fundamental value, funds will enter the market in proportion to their aggressiveness β_i. Due to the "built-in" tendency of the price to revert to its fundamental value, these trades will, on average, be profitable for the funds and more so for funds with greater aggressiveness. Hence, the equity of aggressive funds grows quicker due to a combination of profits and capital reallocation of the fund investor. Importantly, as the equity of funds grows, their market power increases and the volatility of the price decreases.

Aggressive funds are also more likely to leverage to their maximum. Consider an aggressive fund i that has chosen $\lambda_{it-1} = \overline{\lambda}$. Now suppose the price drops such that $\lambda_{it} > \overline{\lambda}$. In response the fund sells parts of its assets as outlined above. Thurner et al. (2012) refer to this forced selling as a margin call as they interpret the leverage constraint as arising from a haircut on a collateralized loan. Recall that the amount the fund will sell is $\Delta A_{it} = \max\{0, (\lambda_{it} - \overline{\lambda})E_{it}\}$, i.e. it is proportional to the fund's equity. As the aggressive fund is likely also the most wealthy fund, its selling can be expected to lead a significant drop in prices. This drop may push other, less aggressive funds past their leverage limits. A margin spiral ensues in which more and more funds are forced to sell into falling markets. In an extreme outcome, most funds will exit or will have lost most of their equity in the price crash. As a result, their market power is limited and the price is dominated by the noise trader. Thus following a margin spiral, price volatility increases due to two forces. First, it spikes due to the immediate impact of the price collapse. But then, it remains at an elevated level due to lack of value investors that push the price towards its fundamental value. These dynamics are illustrated in Fig. 1. These dynamics reproduce some important features of financial time series in a reasonably quantitative way, in particular fat tails in the distribution of returns and clustered volatility (cf. Cont (2001)), as well as a realistic volatility dynamics profile before and after shocks Poledna et al. (2014). These are difficult to reproduce in standard models.

One would expect these dynamics to be less drastic if funds took precautions against margin calls and stayed some $\epsilon > 0$ below their maximum leverage allowing them to more smoothly adjust to price shocks. However, it is important to note that a single "renegade" fund that pushes its leverage limit while all other funds remain well below it, can be sufficient to

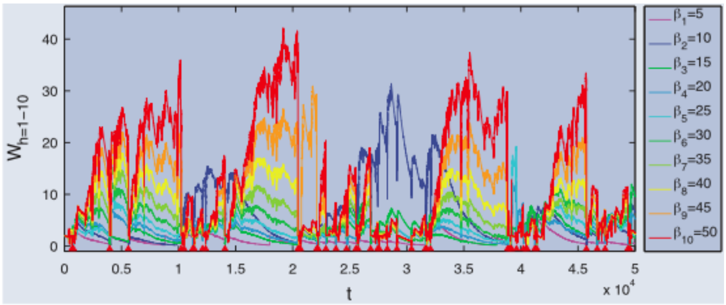


Figure 1: Time series of fund wealth dynamics from Thurner et al. (2012).

cause a margin spiral.

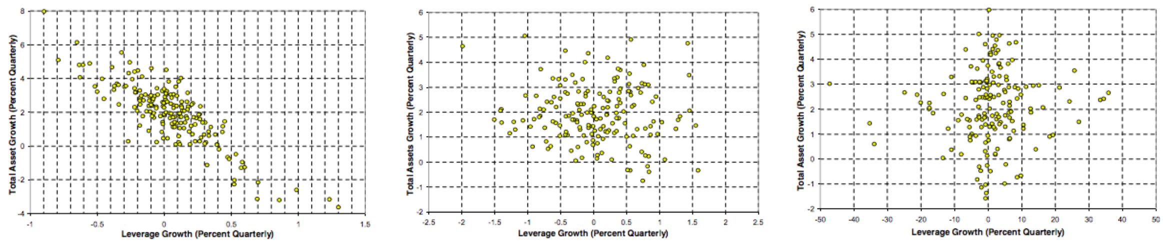
It should be noted that the deleveraging schedule ΔA_{it} that a fund follows can depend on how the leverage constraint is implemented. In Thurner et al. (2012), the leverage constraint results from a haircut applied to a collateralized loan, i.e. the fund obtains a short term loan from a bank, purchases the asset with the loan and its equity and then posts the asset as collateral for the loan. The haircut is equivalent to leverage and determines how much of its assets the fund can finance via borrowing. When the value of the asset drops, the bank will make a margin call as outlined above and the fund will have to sell assets immediately. However, a leverage constraint can, for example, also be imposed by a regulator. In this case, the fund may be allowed to violate the leverage constraint for a few time steps while smoothly adjusting to satisfy the constraint in later periods. Such an implementation will increase the stability of the system. Finally, the schedule $\Delta A_{it} = \max\{0, (\lambda_{it} - \overline{\lambda})E_{it}\}$, assumes the price remains unchanged from the current to the next period. A more sophisticated fund might take its own price impact into account when determining the deleveraging schedule.

3.3 Procyclical leverage and leverage cycles

In the model presented in the previous section, funds actively increase their leverage when the price falls until they reach a leverage limit. Of course, a variety of other leverage management policies are possible. In an effort to study leverage management policies Adrian and Shin (2010*b*) analyze how changes in leverage $\Delta\lambda_t$ relate to changes in total assets ΔA_t (at mark-to-market prices) during the period 1963-2006 for three types of investors: non-financial firms, commercial banks and security broker dealers (such as Goldman Sachs).

For each type of investor the authors find a distinct correlation between leverage and asset changes, see Fig. 2. For non-financial firms changes in leverage are negatively correlated to changes in assets: $\mathrm{Corr}(\Delta\lambda_t, \Delta A_t) < 0$. For commercial banks the two variables are uncorrelated $\mathrm{Corr}(\Delta\lambda_t, \Delta A_t) \approx 0$ and, surprisingly, for broker dealers they find a positive correlation $\mathrm{Corr}(\Delta\lambda_t, \Delta A_t) > 0$. This points towards three distinct leverage management policies.

Non-financial firms appear to be passive investors since leverage decreases when assets appreciate, ceteris paribus. Commercial banks appear to target a specific leverage as leverage



(a) Households (b) Commercial banks. (c) Broker dealers.

Figure 2: Change in total assets vs change in leverage from Adrian and Shin (2010*b*).

changes little as assets change. Such a constant target leverage could arise if the bank faces a constant leverage constraint and chooses to leverage maximally. Finally, suppose an investor has a state contingent target leverage which is high in good times and low in bad times. Let us say that good times are identified by increasing asset prices while bad times are identified by falling asset prices (there are other ways of identifying the state of the world as we will discuss below). In this case, in response to an increase (decrease) in the price of the asset, the investor will increase (decrease) its target leverage and adjust its balance sheet accordingly. Adrian and Shin (2010*b*) call this a *procyclical* leverage policy. With such a leverage policy we expect $\mathrm{Corr}(\Delta\lambda_t, \Delta A_t) > 0$. Hence, it appears that broker-dealers follow a procyclical leverage policy.

A procyclical leverage policy could arise if the broker-dealers face a time varying leverage constraint and choose to leverage maximally. In fact, Adrian and Shin (2010*b*), Danıelsson et al. (2004) and others show that a time varying leverage constraint arises when the investor faces a Value-at-Risk (VaR) constraint as was required under the Basel II regulatory framework. As we will show below, the effect of a VaR constraint is that the investor faces a leverage constraint that is inversely proportionally to market risk. Thus, when market risk is high (low), the leverage constraint is low (high). In this setting the level of risk identifies the state of the world: in good times risk is low while in bad times risk is high.

In summary, three leverage management policies are borne out by the data: passive leverage, constant target leverage and procyclical target leverage. The type of leverage management policy used by the investor can have significant implications for financial stability. Indeed, at least anecdotally, a time series of broker-dealer leverage, perceived risk (as measured by the VIX) and asset prices (as measured by the S&P500) in Fig. 3 suggests a relationship between these three variables which is potentially induced by the dealers' procyclical leverage policy. In the following, we will introduce a model developed by Aymanns and Farmer (2015) that links leverage, perceived risk and asset prices in order to illustrate the effect of procyclical leverage and VaR constraints.

There is a set $\mathcal{B}$ of leveraged value investors (banks for short) and a representative noise trader. There is a risk free asset (cash) and a set $\mathcal{A}$ of risky assets that are traded by banks and the noise trader at discrete points in time $t \in \mathbb{N}$. At the beginning of every period, the banks and the noise trader determine their demand for the assets. For this, each bank i picks a vector $\mathbf{w}_{it}$ of portfolio weights and is assigned a target leverage $\overline{\lambda}_{it}$. The noise trader is not leveraged

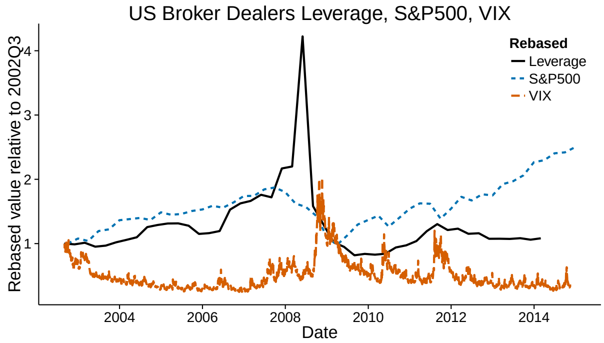


Figure 3: Time series of broker-dealer leverage, perceived risk (as measured by the VIX) and asset prices (as measured by the S&P500) from Aymanns and Farmer (2015).

and therefore only picks a vector $\mathbf{v}_t$ of portfolio weights. Once the agent's demand functions have been fixed the markets for the risky assets clear which fixes prices. Given the new prices banks choose their next period's balance sheet adjustment (buying or selling of assets) in order to hit their target leverage. We refer the reader to Aymanns and Farmer (2015) for a detailed description of the model.

As mentioned above, banks are subject to a Value-at-Risk constraint. Here, a bank's VaR is the loss in market value of its portfolio over one period that is exceeded with probability $1-a$, where a is the associated confidence level. The VaR constraint then requires that bank holds equity to cover these losses, i.e. $E_{it} \geq \text{VaR}_{it}(a)$. We approximate the Value-at-Risk by $\text{VaR}_{it} = \sigma_{it} A_{it}/\alpha$, where σ_{it} is the estimated portfolio variance of bank i and α is a parameter. This relation becomes exact for normal asset returns and an appropriately chosen α. Rearranging the VaR constraint yields the bank's leverage constraint $\overline{\lambda}_{it} = \alpha/\sigma_{it}$. We assume that the bank chooses to be maximally leveraged, e.g. for profit motives. The leverage constraint is therefore equivalent to the target leverage we discussed above. To evaluate their VaR banks compute their portfolio variance as an exponentially weighted moving averages of past log returns.

Let us briefly discuss the implications of this set up. As mentioned at the outset of this section, banks follow a procyclical leverage policy. In particular, the banks' VaR constraint together with its choice to be maximally leveraged at all times, imply a target leverage that is inversely proportional to the banks' *perceived risk* as measured by an exponentially weighted moving average of past squared returns. Why is such a leverage policy procyclical? Suppose, a random drop in an asset's price causes an increase in the level of perceived risk of bank i. As a result the bank's target leverage will decrease (while its actual leverage simultaneously increases) and it will have to sell some of its assets, similar to the funds in the previous section.[6] The banks selling may lead to a further drop in prices and a further increase in perceived risk. In other words, the bank's leverage policy together with its perception of risk can lead to an unstable feedback loop. It is in this sense that the leverage policy is procyclical.

Banks in this model have a very simple, yet realistic, method of computing perceived (or expected) risk. Similar, backward looking methods are well established in practice, see for exam-

[6] Note that this selling will be spread across all assets according to the bank's portfolio weight matrix.

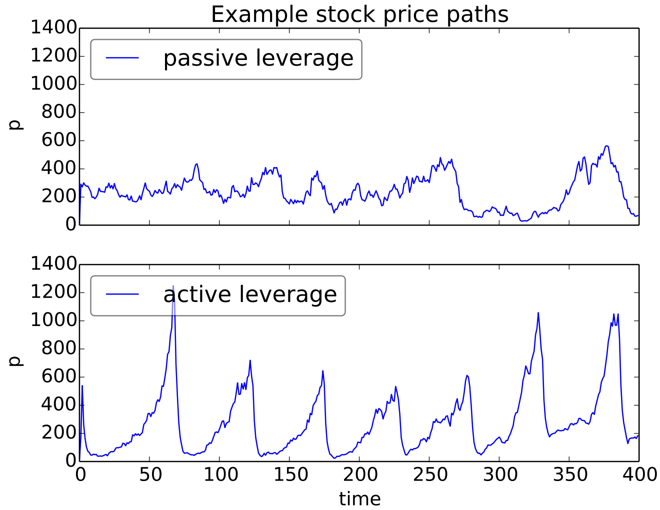


Figure 4: Example paths for a risky asset (stock in the above) from Aymanns and Farmer (2015).

ple Andersen et al. (2006). It is important to note that perceived risk σ_{it} and realized volatility over the next time step can be very different. Since banks have only bounded rationality in this model, their expectations about volatility are not necessarily correct on average.

Let us now consider the dynamics of the model in more detail. In Fig. 4 we show two simulation paths (with the same random seed) of the price of a single risky asset for two leverage policy rules. In the top panel, banks behave like the non-financial firms in Adrian and Shin (2010*b*) — they are passive and do not adjust their leverage to changes in asset prices or perceived risk. In the bottom panel, banks follow the procyclical leverage policy outlined above. The difference between the two price paths is striking. In the case of passive banks, the price follows what appears to be a simple mean reverting random walk. However, when banks follow the procyclical leverage policy, the price trajectory shows stochastic, irregular cycles with a period of roughly 100 time steps. These complex, endogenous dynamics are the result of the unstable feedback loop outlined above. Aymanns and Farmer (2015) refer to these cycles as *leverage cycles*. Leverage cycles are an example of *endogenous* volatility – volatility that arises not because the arrival of exogenous information but due to the endogenous dynamics of the agents in the financial system. To better understand these dynamics consider the state of the system just after a crash has occurred, e.g. at time $t \approx 80$. Following the crash, banks' perceived risk is high, their leverage is low and prices are stable. Over time perceived risk declines and banks increase their leverage. As they increase their leverage, they buy more of the risky assets and push up their prices. At some point leverage is sufficiently high and perceived risk sufficiently low that a relatively small drop of the price of an asset leads to large downward correction in leverage. A crash follows and prices fall until the noise trader's action stops the crash and the cycle begins anew. Naturally, these dynamics depend on the choice of parameters. In particular, when the banks' are small relative to the noise trader, banks trading has no significant impact on asset prices and leverage cycles do not occur. For a detailed discussion of the sensitivity of the results to parameters see Aymanns and Farmer (2015).

These results show that simple behavioral rules, grounded in empirical evidence of bank behavior (Adrian and Shin (2010*b*), Andersen et al. (2006)), can lead to remarkable and unexpected dynamics which bear some resemblance with the run up to and crash following the 2008 financial crises. The results originate from the agents' bounded rationality and their reliance on past returns to estimate their Value-at-Risk. These features would be absent in a traditional economic model in which agents are fully rational. Indeed, rational models rarely display the dynamic instabilities that Aymanns and Farmer (2015) observe. If we believe that real economic actors are rarely fully rational, we should take note of this result. Of course, the agents in this model are really quite dumb. For example, they do not adjust to the strong cyclical pattern in the time series. However, they also live in an economy that is significantly simpler than the real world. Thus their level of rationality in relation to the complexity of the world they inhabit, might not be too far off from real economic agents' level of rationality.

The model discussed above can also yield insights for policy makers on how bank risk management might be modified in order to mitigate the effects of the leverage cycle. Aymanns et al. (2016) present a reduced form version of the model outlined above in order to investigate the implications of alternative leverage policies on financial stability. The authors show that, depending on the size of the banking sector and the properties of the exogenous volatility process, either a constant leverage policy or a Value-at-Risk based leverage policy is optimal from the perspective of a social planner.

4 Contagion in Financial Networks

In analogy to epidemiology, financial contagion refers to the process by which "distress" may spread from one bank to another, where distress can be broadly understood as a bank's distance to insolvency or illiquidity. Typically, financial contagion arises when, via some mechanism or channel, a distressed bank's actions negatively affect some subset of other banks. This subset of banks is said to be connected to the distressed bank. Taken together, the set of all such connections form a network over which financial contagion can spread. Note that there may be multiple channels of contagion, such as interbank loans or derivatives exposures, and the financial networks associated to each channel may differ. In the following, we will discuss the notion of channels of contagion and the associated financial networks more formally.

4.1 Financial linkages and channels of contagion

As mentioned above, the channel (or mechanism) of contagion determines the relevant connections that make up the financial network over which contagion may spread. Depending on the channel, connections in this network may arise directly from bilateral contracts between banks, such as loans, or indirectly via the markets in which the banks operate. In the literature, one typically distinguishes between three channels of contagions: counterparty loss, overlapping portfolio and funding liquidity contagion.[7] Before discussing each channel of contagion in turn, it is helpful to introduce a simple model of a bank's balance sheet.

Suppose there is a set $\mathcal{B}$ of banks in the financial system. Then, as before, the balance sheet of some bank $i \in \mathcal{B}$ is composed of assets A_i, liabilities L_i and equity E_i such that $A_i = L_i + E_i$. It is useful to decompose the bank's assets into three classes: bilateral interbank contracts A_i^B, such as loans or derivative exposures; traded securities A_i^S, such as stocks; and external, unmodeled assets A_i^R whose value is assumed exogenous. Of course we must have that $A_i = A_i^B + A_i^S + A_i^R$. Each asset class can again be decomposed into individual loan contracts, stock holdings and so on. The bank's liabilities can be decomposed in a similar fashion. For now, let us decompose the bank's liabilities simply into bilateral interbank contracts L_i^B, such as loans or derivative exposures, and external, unmodeled liabilities L_i^R which are assumed exogenous. Again we must have that $L_i = L_i^B + L_i^R$ and interbank liabilities can be further decomposed into individual bilateral contracts. Naturally, interbank liabilities are just the flip side of interbank assets such that summing over all banks we must have $\sum_i A_i^B = \sum_i L_i^B$.

With the exception of external assets, the value of the banks' assets depends on the internal state of the financial system. This fact gives rise to the counterparty loss and overlapping portfolio channels of contagion. This is easy to see for the case of counterparty loss contagion and bilateral interbank contracts. Suppose bank i has lent an amount C to bank j such that $A_i^B = L_j^B = C$. Now suppose the value of bank j's external assets A_j^R drops due to some exogenous shock. As a result, the probability of default of bank j is likely to increase. In some way or another, the probability of default of bank j will affect the value of the claim A_i^B that bank i holds on bank j. If bank i's interbank assets are marked to market, that is their value is recomputed in every period based on market prices, a change in bank j's probability of default will affect the market value of A_i^B. In the worst case, if bank j defaults, bank i will only recover some fraction $r < 1$ of its initial claim A_i^B. If the loss of bank i exceeds its equity, i.e. $(1-r)A_i^B > E_i$ bank i will default as well.[8] Now, how can this lead to financial contagion? To elaborate on the above toy example, suppose that bank i in turn borrowed an amount C from another bank k such that $A_k^B = L_i^B = C$. In this scenario, it can be plausibly argued that an increase in the probability of default of j increases the probability of default of i which in turn increases the probability of default of k. If all banks mark their books to market, an initial shock to j can therefore end up affecting the value of the claim that bank k holds on bank i. Again, in the extreme scenario, the default of bank j may cause bank i to default which may cause bank k to default. This is the essence of counterparty loss contagion. Naturally, in a real financial system the structure of interbank contracts will be much more complex than in the toy example outlined above. The financial network associated with the counterparty loss contagion channel is therefore the network induced by the set of interbank liabilities.

The overlapping portfolio channel is slightly more subtle. Suppose bank i and bank j have both invested an amount C in the same security l such that $A_{il}^S = A_{jl}^S = C$, where we

[7] Information contagion (cf. Acharya and Yorulmazer (2008)) is another channel of contagion but won't be discussed in this section.

[8] In reality this scenario is excluded due to large exposure limits which require that $A_i^B < E_i$.

have introduced the additional index to reference the security. Now suppose the value of bank j's external assets A_j^R drops due to some exogenous shock. How will bank j respond to this loss? In the extreme case, when the exogenous shock causes bank j's bankruptcy ($E_i < 0$), the bank will liquidate its entire investment in the security. However, even if the bank does not go bankrupt, it may wish to liquidate some of its investment. This can occur for example when the bank faces a leverage constraint as discussed in Section 3. Bank j's selling is likely to have price impact. As a result, the market value of A_{il}^S will fall. If bank i also faces a leverage constraint, or even goes bankrupt following the fall in prices, it will liquidate part of its securities portfolio in response. How will this lead to contagion? Suppose that bank i also has invested an amount C into another security m and that another bank k has also invested into the same security, such that $A_{im}^S = A_{km}^S = C$. If bank i liquidates across its entire portfolio, it will sell some of security m following a fall in the price of security l. The resulting price impact will then affect the balance sheet of bank k which was not connected to bank j via an interbank contract or a shared security. This is the essence of overlapping portfolio contagion. Banks are linked by the securities that they co-own and the fact that they liquidate with market impact across their entire portfolios. Empirical evidence from the 2007 Quant meltdown for this contagion channel has been provided in Khandani and Lo (2011).

Funding liquidity contagion often occurs in conjunction with overlapping portfolio contagion and can be seen as the complement to counterparty loss contagion. To see this, let us reconsider the scenario we discussed for counterparty loss contagion. Suppose bank i has lent an amount C to bank j such that $A_i^B = L_j^B = C$. As before, suppose the value of bank j's external assets A_j^R drops due to some exogenous shock and as a result, the probability of default of bank j increases. Now, suppose that every T periods bank i can reevaluate and decide whether to roll over its loan to bank j. Further assume that bank i is bank j's only source of interbank funding and L_j^R is fixed. Given bank j's increased default probability, bank i may choose not to roll over the loan at the next opportunity. Ignoring interest payments, if bank i does not roll over the loan, bank j will have to deliver an amount C to bank i. In the simplest case, bank j may choose not to roll over its own loans to other banks which in turn may decide against rolling over their loans. This is the essence of funding liquidity contagion. As for counterparty loss contagion, the associated financial network is induced by the set of interbank loans. Empirical evidence on the fragility of funding markets during the past financial crisis has been provided for example in Afonso et al. (2011), Iyer and Peydro (2011). In a further complication, bank j may also choose to liquidate part of its securities portfolio in order to pay back its loan. Funding liquidity contagion can therefore lead to overlapping portfolio contagion and vice versa. This interdependence of contagion channels makes the funding liquidity and overlapping portfolio contagion processes the most challenging from a modeling perspective.

In the remainder of this section we will discuss models for counterparty loss, overlapping portfolio and funding liquidity contagion as well as models for the interaction of all three contagion channels.

4.2 Counterparty loss contagion

Consider a set of banks $\mathcal{B}$, with $N = |\mathcal{B}|$, and a matrix of nominal interbank liabilities L. Banks hold interbank assets $A_i^B = \sum_j L_{ij}^T$ and external assets A_i^R which can be liquidated at no cost. Banks have interbank liabilities $L_i^B = \sum_j L_{ij}$ only. All interbank liabilities mature at the same time. Now suppose banks are subject to a shock $s_i \geq 0$ to the value of their external assets such that $\hat{A}_i^R = A_i^R - s_i$. Given an exogenous shock, we can ask a number of questions. First, which loan payments are feasible given the exogenous shock? Second, which banks will default on their liabilities? And finally, how do the answers to the first two questions depend on the structure of the interbank liabilities L. There is a large literature that studies counterparty loss contagion in a set up similar to the above, including Gai and Kapadia (2010), Elliott et al. (2014), Acemoglu et al. (2015), Battiston et al. (2012) and Amini et al. (2013). In the following, we will briefly introduce the seminal contribution by Eisenberg and Noe (2001), who provide a solution to the first two questions. We will then consider a number of extensions of Eisenberg and Noe (2001) and alternative approaches to addressing the above questions.

Define the relative, nominal, interbank liabilities matrix as $\Pi_{ij} = L_{ij}/L_i^B$ for $L_i^B > 0$ and $\Pi_{ij} = 0$ otherwise. The relative liabilities matrix corresponds to the adjacency matrix of the weighted, directed network $\mathcal{G}$ of interbank liabilities. Let $\mathbf{p} = (p_1, \ldots, p_N)$ denote the vector of total payments made by the banks when their liabilities mature. Naturally, a bank pays at most what it owes in total, i.e. $p_i \leq L_i^B$. However, it may default and pay less if the value of its external assets plus the payments it receives from its debtors is less than what it owes. The individual payments that bank i makes are given by $\Pi_{ij} p_i$. The vector of payments, also known as the clearing vector, that satisfies these constraints is the solution to the following fixed point equation

$$p_i = \min\{L_i^B, \hat{A}_i^R + \sum_j \Pi_{ij}^T p_j\}. \tag{1}$$

Eisenberg and Noe (2001) show that such a fixed point always exists. In addition, if within each strongly connected component of $\mathcal{G}$ there exists at least one bank with $\hat{A}_i^R > 0$, Eisenberg and Noe (2001) show that the fixed point is unique. In other words, there exists a unique way in which losses incurred due to the adverse shock $\{s_i\}$ are distributed in the financial system via the interbank liabilities matrix. It is important to note that in this set up losses are only redistributed – contagion acts as a distribution mechanism but does not, in the aggregate, lead to any further losses to bank shareholders beyond the initial shock. To see this define the equity of bank i prior to the exogenous shock as $E_i = A_i^B + A_i^R - L_i^B$ and after the exogenous shock as $\hat{E}_i = \hat{A}_i^B(\mathbf{p}) + A_i^R - s_i - \hat{L}_i^B(\mathbf{p})$. Note that post shock both bank i's assets and liabilities depend on the clearing vector $\mathbf{p}$. Taking the difference and summing over all banks we obtain $\sum_i E_i - \hat{E}_i = \sum_i A_i^R - (A_i^R - s_i) = \sum_i s_i$ since $\sum_i A_i^B = \sum_i L_i^B$ and $\sum_i \hat{A}_i^B(\mathbf{p}) = \sum_i \hat{L}_i^B(\mathbf{p})$. Also note that, while bank shareholder losses are not amplified, losses to the total value of bank assets are amplified due to indirect losses, i.e. $\sum_i A_i^B - \hat{A}_i^B(\mathbf{p}) + s_i \geq \sum_i s_i$. Some authors argue that this is a more appropriate measure of systemic impact of the exogenous shock than bank shareholder loss, see Glasserman and Young (2015). Finally note that the mechanism of finding a clearing vector removes any potential frictions in the financial system and ensures that the

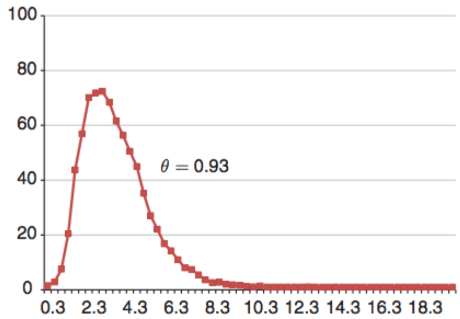


Figure 5: Expected number of defaults as a function of diversification in Elliott et al. (2014).

maximal payment is made given the exogenous shocks. Other authors have argued that this is too optimistic and assume instead that once a default has occurred, some additional bankruptcy costs are incurred, see for example Rogers and Veraart (2013) and Cont et al. (2010). In this case aggregate bank shareholder losses may be larger than the aggregate exogenous shock.

The clearing vector and the associated number of defaulting banks, given an exogenous shock and a nominal interbank liabilities matrix L, can be computed via the following simple default cascade algorithm. First, initialize a payment vector $\mathbf{p} = \mathbf{L}^B$. Then update its entries p_i based on Eq. (1) for all i, each iteration taking the previous iteration's payment vector as input to the right hand side of Eq. (1). Repeat this process until convergence. A well known result is that, as banks' interbank lending A_i^B becomes more diversified over $\mathcal{B}$, the expected number of defaulting banks first increases and then decreases, see Fig. 5. If banks lend only to a very small number of other banks, the network is not fully connected. Instead it consists of several, small and disjoint components. A default in a particular component cannot spread to other components hence limiting the size of the default cascade. As banks become more diversified, the network will become fully connected and default cascades can spread across the entire network. As banks diversify further, the size of the individual loans between banks declines to the point that the default of any one counterparty becomes negligible for a given bank. Thus default cascades become unlikely. However, if they do occur, they will be very large. This is often referred to as the "robust-yet fragile" property of financial networks, see for example Gai and Kapadia (2010) and Amini et al. (2013) who show this property for large financial networks via a branching process approximation.

The model and solution method in Eisenberg and Noe (2001) are very simple and reduce to finding a fixed point payment vector. Other models of counterparty contagion, for example Gai and Kapadia (2010), Amini et al. (2013) or Battiston et al. (2012), also rely on finding a fixed point, albeit numerically in the latter case. These equilibrium models often form the starting point for heterogeneous agent models that try to incorporate additional dynamic effects and more realism into the counterparty loss contagion process, see for example Georg (2013) where the effect of a central bank on the extent of default cascades is studied.

Finally, note that it is widely believed that large default cascades are quite unlikely for reasonable assumptions about the distribution of the exogenous shock and nominal interbank liabilities matrix, see for example Glasserman and Young (2015). For larger cascades to occur, default costs or additional contagion channels are necessary. Nevertheless, the existence of a counterparty loss contagion channel is important in practice as it affects the decisions of agents, for example in the way they form lending relationships. In other words, while default cascades are unlikely to occur in reality, they form an "off-equilibrium" path that shapes reality, see Elliott et al. (2014).

4.3 Overlapping portfolio contagion

Consider again a set of banks $\mathcal{B}$, with $N = |\mathcal{B}|$. There is an illiquid asset whose value is exogenous and a set of securities $\mathcal{S}$, with $M = |\mathcal{S}|$, traded by banks at discrete points in time $t \in \mathbb{N}$. Let $\mathbf{p}_t = (p_{1t}, \dots, p_{Mt})$ denote the vector of prices of the securities and let the matrix $\mathbf{S}_t$ denote the securities ownership of all banks at time t. The assets of bank i are then given by $A_{it} = \mathbf{S}_{it} \cdot \mathbf{p}_t + A_i^R$, where A_i^R is the bank's illiquid asset holding. Let E_{it} and $\lambda_{it} = A_{it}/E_{it}$ denote bank i's equity and leverage, respectively.

As mentioned above, overlappping portfolio contagion occurs when one bank is forced to sell and the resulting price impact forces other banks with similar asset holdings to sell. What might force banks to sell? In an extreme scenario, a bank might have to liquidate its portfolio if it becomes insolvent, i.e. $E_{it} < 0$. This is the approach taken in Caccioli et al. (2014). But even before becoming insolvent, a bank might be forced to liquidate part of its portfolio if it violates a leverage constraint $\overline{\lambda}$ as we have shown in Section 3. This is the approach taken in Cont and Schaanning (2014), where banks liquidate part of their portfolio if their leverage exceeds their leverage constraint. Other papers that discuss the effects of overlapping portfolios include Duarte and Eisenbach (2015), Greenwood et al. (2015), Cont and Wagalath (2016, 2013). Let us first discuss the simpler case without a leverage constraint.

Suppose bank i is subject to an exogenous shock $s_i > 0$ that reduces the value of its illiquid assets to $\hat{A}_{it}^R = A_{it}^R - s_i$. If $s_i > E_{it}$ the bank becomes insolvent and liquidates its entire portfolio. Let $Q_{jt} = \sum_{i \in \mathcal{I}_t} S_{ijt}$ denote the total amount of security j that is liquidated by banks in the set $\mathcal{I}_t$ of banks that became insolvent at time t. The sale of the securities is assumed to have market impact such that $p_{jt+1} = p_{jt}(1 + f_j(Q_{jt}))$, where $f_j(\cdot)$ is the market impact function of security j. Caccioli et al. (2014) assume an exponential form $f_j(x) = \exp(-\alpha_j x) - 1$ where $\alpha_j > 0$ is chosen to be inversely proportional to the total shares outstanding of security j. In the next period, banks reevaluate their equity at the new securities prices. The change in equity is equal to $\Delta E_{it+1} = \sum_j S_{ijt} f_j(Q_{jt}) - s_i$. Note that in this setting we hold S_{ijt} fixed unless a bank liquidates its entire portfolio. Thus banks who share securities with the banks that were liquidating in the previous period will suffer losses due to market impact. These losses may be sufficiently large for additional banks to become insolvent. If this occurs contagion will spread and more banks will liquidate their portfolios leading to further losses. Over the course of this default cascade, banks may suffer losses that did not share any common securities with the initially insolvent banks.

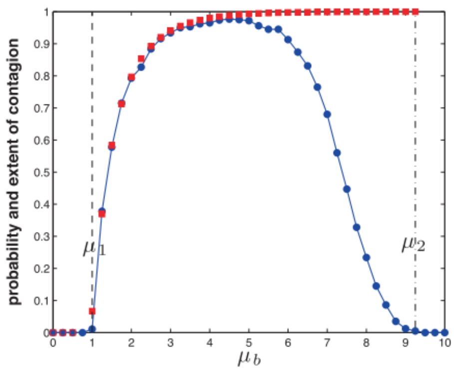


Figure 6: Expected number of defaults as a function of diversification in Caccioli et al. (2014).

The evolution of the default cascade outlined above can be easily computed numerically by following the procedure outlined above until no further banks default. Caccioli et al. (2014) also show that the default cascade can be approximated by a branching process provided suitable assumptions are made about the network structure. For their computations, Caccioli et al. (2014) assume that a given bank i invests into each security with a fixed probability μ_B/M, where μ_B is the expected number of securities that a bank holds. The bank distributes a fixed investment over all securities it holds. When μ_B/M is high, the portfolios of banks will be highly overlapping, i.e. banks will share many securities in their portfolios. Similar to the results for counterparty loss contagion, the authors find that as banks become more diversified, that is μ_B increases while M is held fixed, the expected number of defaulting banks first increases and then decreases, see Fig. 6. The intuition for this result is again similar to the counterparty loss contagion case. If banks are not diversified, their portfolios are not overlapping and price impact from portfolio liquidation of one bank affects only a few banks. As banks become more diversified, their portfolios become more overlapping and price impacts spreads throughout the set of banks leading to large default cascades. Eventually, when they become sufficiently diversified, the losses resulting from a price change in an individual security become negligible and large default cascades become unlikely. However, when they do occur, they encompass the entire set of banks. Thus, here again the financial network displays the robust-yet fragile property. Interestingly, the authors also show that for a fixed level of diversification, there exists a critical bank leverage λ_{it} at which default cascades emerge. The intuition for this result is that, when leverage is low, banks are stable and large shocks are required for default to occur, as leverage grows banks become more susceptible to shocks and defaults occur more easily.

As mentioned above, banks are likely to liquidate a part of their portfolio even before bankruptcy, if an exogenous shock pushes them above their leverage constraint. This is the setting studied in Cont and Schaanning (2014). In this case, the shocks for which banks start to liquidate as well as the amount liquidated are both smaller than in the setting discussed above. If banks breach their leverage constraint due to an exogenous shock s_i to the value of their illiquid assets, Cont and Schaanning (2014) require that banks liquidate a fraction Γ_i of their entire portfolio such that $((1-\Gamma_i)\mathbf{S}_{it} \cdot \mathbf{p}_t + \hat{A}^R_{it})/E_{it} = \overline{\lambda}$. The corresponding liquidated monetary amount for a security j is then $Q_{jt} = \sum_{i \in \mathcal{B}} \Gamma_i S_{ijt} p_{jt}$. Again, the sale of the securities is assumed to have market impact such that $p_{jt+1} = p_{jt}(1 + f_j(Q_{jt}))$. However, in contrast to Caccioli et al. (2014), the authors assume that the market impact function $f_j(x)$ is linear in x, where x is the total monetary amount sold rather than the number of shares. Similar market impact functions are used by Greenwood et al. (2015) and Duarte and Eisenbach (2015). Indeed the shape and parameterization of the market impact function is crucial for the impact of fire sales. Only if markets are sufficiently illiquid will fire sales leads to contagion. So far, most models take market liquidity, i.e. the market impact parameter, as exogenously given (one exception is Brunnermeier and Pedersen (2009)). Hence, endogenizing market liquidity remains an important challenge.

While the results of Cont and Schaanning (2014) are qualitatively quite similar to Caccioli et al. (2014), the former calibrate their model to realistic portfolio holdings and market impact parameters and are hence able to obtain quantitative estimates of the extent of losses due to overlapping portfolio contagion. As such their contribution provides a good starting point for more sophisticated financial system stress tests that will be discussed in the following sections. The above outlined models can be improved in many ways. In one interesting attempt, Cont and Wagalath (2016) study the effect of overlapping portfolios and fire sales on the correlations of securities in a continuous time setting, where securities prices follow a stochastic process rather than being assumed fixed up to the price impact from fire sales.

4.4 Funding liquidity contagion

Both counterparty loss and overlapping portfolio contagion involved essentially no strategic decisions. Instead agents simply reacted to constraints and contractual obligations. In principle, funding liquidity contagion could be modeled in a similar way. For example, when banks need to deleverage, they not only sell assets but also refuse to roll over short term loans to other banks. This can lead to a funding liquidity cascade. Traditionally though, the withdrawal of funding, i.e. a bank run, is modeled as a coordination game, see Diamond and Dybvig (1983). If in addition lenders have private information, these coordination games can be solved using global games, see Morris and Shin (2001). In this framework, given the right conditions, funding liquidity cascades can be self-fulfilling. As mentioned above, most heterogeneous agent models abstract from strategic interactions. One notable exception that tries to combine both strategic interactions and network effects is Anand et al. (2015).

4.5 Interaction of contagion channels

So far we have focused on counterparty loss and overlapping portfolio contagion in isolation. Of course, focusing on one channel in isolation only provides a partial view on the system and thus ignores important interaction effects. Indeed, it has been shown by a number of authors that the interaction of contagion channels can substantially amplify the effect of each individual channel leading. Constructing models with multiple contagion channels is tricky yet some progress has been made.

Caccioli et al. (2015) and Cifuentes et al. (2005) study the interaction of counterparty loss and overlapping portfolio contagion by combining variants of the contagion processes outlined above into a comprehensive simulation model. In particular, using data from the Austrian interbank system Caccioli et al. (2015) show that the expected size of a default cascade, conditional on a cascade occurring, can increase by orders of magnitude if overlapping portfolio contagion occurs alongside counterparty loss contagion rather than in isolation.

In a very simple model, Brunnermeier and Pedersen (2009) argue theoretically how mechanisms behind funding liquidity and overlapping portfolio contagion can amplify each other. Kok and Montagna (2013) combine the work all of the above authors and construct a model in which counterparty loss, overlapping portfolio and funding liquidity contagion interact. Such comprehensive stress testing models are the subject of the remainder of this paper and will be discussed in detail in the following sections, see Section 5.

5 Models in Policy: Stress Tests as a Tool for Macroprudential Policy Making

The insights from the models discussed so far are increasingly used in the design of tools for assessing and monitoring financial stability. In this section, we will discuss the most striking of these tools; financial stress tests. By combining insights from various systemic risk models and linking those to policy, stress tests give traction to the thinking discussed so far. In this section, we first outline the functions and types of stress tests, and then provide an overview and evaluation of current micro- and macroprudential stress tests.

5.1 Background and Purpose

Stress tests are designed to assess the resilience (or fragility) of a financial institution, market, or contract, or even of the financial systems as a whole, under hypothetical but plausible stressed circumstances (Siddique and Hasan 2012, Scheule and Roesh 2008, Quagliariello 2009, Moretti, Stolz and Swinburne 2008). At its core, this implies that a stress test is a simulation that runs under a set of parameters that, together, are referred to as "scenarios". These scenarios can take many forms, including general economic shocks (such as a drop in housing prices or a rise in the unemployment rate) and financial shocks (the collapse of a major financial institution). On the basis of detailed information about the institution or sector under investigation, stress tests evaluate the resilience (or fragility) of the institution under investigation for each of these scenarios, providing valuable insights to regulators and market participants.

Stress tests are a relatively novel part of the regulatory toolkit. The potential utility of stress tests had been extensively discussed in the years preceding the financial crisis, and stress tests were in fact used by the International Monetary Fund to evaluate the robustness of countries' financial systems. But it was only during the financial crisis that they were used on a large scale.

In February 2009, with uncertainty about the capitalization of banks still paramount, the U.S. Treasury Department led by Timothy Geithner introduced the Supervisory Capital Assessment Program (SCAP) (Schuermann 2014, Geithner 2014). Under the auspices of this program, the Federal Reserve Board created a stress test and required the U.S.' 19 largest banks to apply it. The immediate motivation was to determine how much capital a bank would need to ensure its viability even under adverse scenarios, and - relatedly - whether capital injections from the U.S. tax payer were needed. A secondary motivation was to reduce uncertainty about the financial health of these banks, and thereby to calm the markets and restore confidence in the U.S. financial markets (Anderson 2016, Tarullo 2016). In an environment marked by suspicion about the financial health of large banks, a tool was needed that would bridge informational asymmetries and credibly showcase their resilience to potential shocks.

In later years, SCAP was replaced by the Comprehensive Capital Analysis and Review (CCAR) and the Dodd-Frank Act Stress Test (DFAST), which have been run on an annual basis since 2011 and 2013, respectively (FED 2017*b*,*a*). These early stress tests gave investors and regulators, as well as the public at large, insight into previously opaque balance sheets of banks. They have been credited with restoring trust in the financial sector, and thereby contributing to the return of normalcy in the financial markets (Bernanke 2013).

Across the Atlantic, European authorities followed suit and introduced a stress test of their own (EBA 2017*a*). This resulted in the first EU stress tests in 2009, overseen by the Committee of European Banking Supervisors (CEBS) (Acharya, Engle and Pierret 2014). Due to concerns about their credibility (Ong and Pazarbasioglu 2014), the CEBS stress test was replaced in 2011 by stress tests conducted by the European Banking Authority (EBA). These have been maintained ever since (EBA 2017*b*).

In 2014, the Bank of England also introduced stress tests in line with the American example (Ban 2014). Around that time, stress tests became a widely used regulatory tool in other countries too (Boss, Krenn, Puhr, Schwaiger et al. 2007), and are regarded as a cornerstone of the post-crisis regulatory and supervisory regime. Daniel Tarullo, who served on the board of the U.S. Federal Reserve from 2009 to 2017 and was responsible for the implementation of stress tests in the U.S., has hailed stress tests as "the single most important advance in prudential regulation since the crisis" (Tarullo 2014).

Stress tests, however, are not a uniform tool. They can take a variety of forms, which can be helpfully classified along two dimensions. The first dimension concerns their object; does the stress test only cover banks, or non-banks as well? In the early days of stress testing, only banks were considered, but now there is an increasing trend towards including non-banks as well. Given the composition of the financial system in most advanced economies, and the importance of non-banks in these financial systems, it is increasingly acknowledged that these institutions can generate systemic risk too. In the United Kingdom, for example, almost half of the assets in the financial system are held by non-banks (Burrows, Low and Cumming 2015), as is illustrated by the map of the UK financial system depicted in Figure 7.

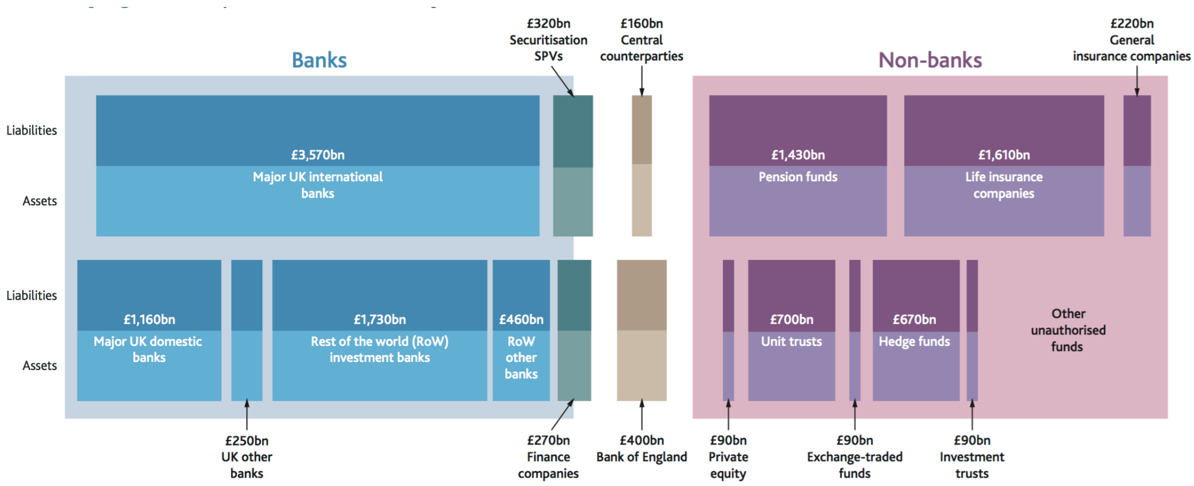


Figure 7: Map of the UK financial system. Source: Burrows et al. (2015).

The second dimension concerns the scope of the stress test. *Microprudential* stress tests focuses on the resilience of invidual financial institutions (Siddique and Hasan 2012, Scheule and Roesh 2008, Quagliariello 2009, Moretti, Stolz and Swinburne 2008), whereas *macroprudential* stress tests assess the resilience of a larger group of financial institutions, or even of the whole financial sector (Cetina, Lelyveld and Anand 2015, Bookstaber, Cetina, Feldberg, Flood and Glasserman 2014). The latter type takes feedback loops and interactions between financial institutions into account, whereas the former does not.

This section will proceed by discussing the most important stress tests in each category, starting out with the microprudential stress tests and moving on to macroprudential stress test - in both cases focusing on banks first, and non-banks second. For each case, we will discuss, with some abstraction, the methodology and models used, and evaluate the strengths and weaknesses of the approach taken.

5.2 Microprudential Stress Tests

5.2.1 Microprudential Stress Test of Banks In general terms, the process of conducting microprudential stress tests takes the following three steps. First, the designated regulator designs an initial stressed scenario, which stipulates a crisis narrative and an associated set of exogenous shocks. This scenario is designed in such a way that it is adverse, plausible, and coherent (Siddique and Hasan 2012, Scheule and Roesh 2008, Quagliariello 2009, Moretti, Stolz and Swinburne 2008). In other words, the scenario must capture a crisis tail event that is not wholly inconceivable. The set of shocks must be chosen such that they do not violate the relationships among variables historically observed or deemed conceivable. For example, the shocks would typically not simultaneously include a downward shock in GDP and an downward shock unemployment. Typically, the exogenous shocks comprise shocks to a set of macro-variables, such as equity prices, house prices, unemployment rate, and GDP, and financial variables, such as interest rates and credit spreads.

Second, when the scenario has been determined, its effect on the balance sheet of banks is determined (depending on the regime, these calculations are either made by the regulator or by banks themselves) to calculate the post-stress regulatory capital ratio[9] and profits. This calculation is based on an evaluation of how the shocks change the values of the assets and liabilities on the balance sheet as well as expected income. Such value changes on the balance sheet materialize either through a re-evaluation of the market value (if the asset or liability is marked-to-market), or through a credit shock re-evaluation. Typically, the first two are captured by market risk models and credit risk models, such as those described in (Siddique and Hasan 2012, Scheule and Roesh 2008, Quagliariello 2009, Moretti, Stolz and Swinburne 2008). The size of the credit loss is typically computed by multiplying the loss given default (LGD), the probability of default (PD) and the exposure at default (EaD). Estimating these variables is therefore key to the credit risk component of stress testing (Foglia 2008). Value changes in expected income materialize through shocks that affect income, such as interest rate shocks. The "stressed income" (in other words: the retained earnings) feeds into the stressed regulatory capital. The post-stress regulatory capital, after all, is the post-stress retained earnings plus regulatory capital over the stressed risk-weighted assets.

Stress tests must not only compute post-stress values of assets, liabilities, and income, but also the post-stress risk weights[10]. Capital ratios are commonly calculated relative to risk-weighted assets (RWAs), rather than total assets, and in stress these risk-weights can change. To determine this change, stress tests can either include the stressed risk-weights of the standards approach, or use those calculated based on the internal models of banks (Capgemini 2014).[11]

Third, once the post-stress capital ratio has been determined, it is compared to a hurdle rate set by the regulator. If it does not meet this hurdle rate, the bank is said to have failed the stress test. In such circumstances, the regulator commonly has the authority to require the bank to raise extra capital. Microprudential stress tests are thus used as a tool to recapitalize undercapitalized banks, thereby reducing their leverage and increasing their resilience.

5.2.2 Microprudential Stress Test of Non-Banks

5.2.2.1 General Methodology Given the importance of particular non-bank financial institutions to the financial system (FSB 2015, ECB 2015, Burrows, Low and Cumming 2015, Pozsar, Adrian, Ashcraft and Boesky 2010, Pozsar and Singh 2011, Mehrling, Pozsar, Sweeney and Neilson 2013, Pozsar 2013), it was only a matter of time before the scope of stress tests would be extended beyond banks. So far, at least three types of non-banks have been subjected to stress tests; insurers, pension funds and central clearing parties (CCPs). By examining representative stress tests for each of these three institutions, this section illustrates the methodology applied. In each of the cases, the scenario design is similar to that for banks – so we will limit ourselves to the methodological components that are particular to the stress test

[9] The tier I capital ratio is equal to the tier I equity value of a bank over its risk-weighted assets.
[10] Risk-weights, weight the on or off-balance sheet assets of a bank according to its riskiness.
[11] The methodology to compute the risk-weights based on the standards approach is found in (BIS 2015*a*).

of each type of institution.

5.2.2.2 Insurers and Pension Funds

Insurance stress tests have been conducted by the Bank of England (BoE 2015), the FSAP program of the IMF (Jobst 2014), the Federal Reserve (Accenture 2015, Robb 2015), and the European Insurance and Occupational Pensions Authority (EIOPA) (EIOPA 2016). Pension fund stress tests have been conducted by the International Organisation of Pension Fund Supervisors (IOPFS) (Ionescu and Yermon 2014) and EIOPA (EIOPA 2017). The general methodology of the insurer and pension fund stress tests will be illustrated using the EIOPA insurer stress tests and EIPOA pension fund stress test, respectively.

Its 2016 stress test of (life-) insurers tested the impact of the initial scenario on the asset of liability (AoL) ratio of insurers (EIOPA 2016). The AoL ratio helps inform whether insurers will have sufficient assets to meet their insurance liabilities. In addition, the stress test included a cash flow analysis to investigate the degree to which the timing of insurers' cash inflows coming from assets matched the insurers' expected outflows due to insurance liabilities. Instead of revealing the results of the stress tests for individual institutions, they were published as aggregate results to indicate the vulnerability of the insurance sector on a country or EU-wide level.

Its 2015 stress test of (occupational) pension funds assessed the resilience of defined benefit (DB) and hybrid pension schemes against adverse market scenarios. It also assessed increase in life expectancy as well as to identify potential vulnerabilities of defined contribution (DC) schemes.

5.2.2.3 Central Clearing Parties

Central clearing parties (CCPs) step into bilateral trades by means of novation, becoming the buyer to every seller and the seller to every buyer (Cont 2015, Murphy 2013, Duffie, Scheicher and Vuillemey 2015, Duffie and Zhu 2011). In doing so, they take on counterparty credit risk which they subsequently mitigate, thereby insulating members from default losses. To absorb such losses, CCPs have an elaborate "default waterfall", which stipulates exactly how losses are absorbed, and who bears that burden (Murphy 2013, Capponi, Cheng and Rajan 2015). The default waterfall consists of various layers of collateral (e.g. initial margin, variation margin, default fund contributions) and some equity. Generally, to absorb losses initial and variation margins posted by the counterparties of the CCP, the so-called clearing members (CMs), are drawn upon first. The value of the initial margin is set so that upon the default of a clearing member its positions can be unwound without incurring a loss. However, market conditions can change, so to achieve the same result even if conditions change an additional variation margin is charged. If losses exceed the margin posted by the defaulted clearing members, the CCP uses its equity to absorb further losses. Such "skin in the game" is meant to ensure that the CCP engages in prudent risk management, including by requiring sufficiently high margins instead of aggressively lowering margins to attract new business.

If losses exceed the CCP's equity, losses are absorbed by default fund contributions of other clearing members. In such cases, clearing members whose default contributions are hit experience a hit to their equity, as they are required to replenish the default fund contributions. If default fund contributions are still insufficient to cover the losses, the CCP can require its clearing members to make further contributions to the default fund, typically in the form of cash. Clearing members might not be able to post such additional collateral, especially not in times of stress, and it is therefore unclear whether this last line of defense is credible (Cont 2015). Finally, if the entire default waterfall is insufficient to cover the losses, the CCP itself defaults.

Given the high volume of trades larger CCPs process, their failure is generally thought to have catastrophic consequences for the financial system (ESMA 2015, Murphy 2013). After the financial crisis, their importance has only grown, since it has become mandatory to clear certain derivatives, in jurisdictions, such as the EU and the US (ESMA 2017, EY 2013), through CCPs. Although this has brought down bilateral exposures (Cont and Kokholm 2014), it has concentrated exposures in CCPs.

The critical role CCPs fulfil has prompted regulators to create CCP-specific stress tests to assess whether their default waterfall can absorb losses even under extreme circumstances. CCP stress tests have been conducted by the commodity futures and trading commission (CFTC) in the US (CFTC 2016), the German and British regulatory authorities (Erbenova 2015) (will include a US regulator in 2017 (Robb 2015)), and the European Securities and Markets Authority (ESMA). We will use the ESMA methodology to illustrate how the process can be designed (ESMA 2015).

In the 2015 scenario, the CCP's two largest clearing members (those with the largest exposure to the CCP's default fund) were assumed to default[12] when simultaneously a severe adverse market shift hit.[13] Because clearing members often trade in multiple CCPs, the two defaulted clearing members for each CCP were assumed to default in all CCPs where they cleared – which is referred to as "cross default contagion".

Following the scenario design, the losses to each step of the default waterfall are calculated. If there are losses beyond the absorption capacity of the default waterfall, those are calculated too. Taken together, these insights are used to make a judgment about the capitalization of the CCP.

Further, an attempt was done to compute the contagion effects following the initial scenario. This was done by computing the hit to equity of the non-defaulted clearing members in case

[12] This scenario tests the default of the two largest clearing members per CCP. It translates at EU level the cover 2 principle established in Article 43 of EMIR and Article 53 (1) of the RTS (Regulation EU No 153/2013), which states: "A CCP's stress-testing programme shall ensure that its combination of margin, default fund contributions and other financial resources are sufficient to cover the default of at least two clearing members to which it has the largest exposures under extreme but plausible market conditions."

[13] It is important that both the default of two counterparties and a severe adverse market shift hit simultaneously. If two clearing members default, but there is no market shift, the total margin posted should be sufficient to absorb all losses of the defaulted clearing members. If only the market conditions change, the CCP is not at risk of default because its variation margin ensures it is not exposed to changes in market conditions.

the initial scenario caused the default fund contributions of the non-default clearing members to be affected. If the hit to equity of a non-defaulted clearing member would exceed a threshold percentage of the non-defaulted CM's equity, that clearing member would be identified to be at vulnerable to such a scenario. If the hit to the CM's equity would wipe out all its equity, it was said to default.

5.2.3 Strengths and Weaknesses of Current Microprudential Stress Tests Microprudential stress tests add value in at least three ways. First, they give market participants more insight into the opaque balance sheets of the financial institutions being evaluated (Bookstaber, Cetina, Feldberg, Flood and Glasserman 2014). Opacity coupled with asymmetric information can, especially in times of financial distress, lead to a loss of confidence (Diamond and Dybvig 1983, Brunnermeier 2008). After all, if the type and quality of a financial institution's assets and liabilities are unclear, outsiders may conceivably fear the worst and, for example, pull back their funding (Akerlof 1970). Such responses feed speculative runs which can turn into self-fulfilling prophecies and, ultimately, (further) destabilize the financial system at the worst possible time (He and Xiong 2012, Diamond and Dybvig 1983, Martin, Skeie and Von Thadden 2014, Copeland, Martin and Walker n.d.). Credibly executed microprudential stress tests provide insight into an institution's balance sheet, and can signal confidence about the institution's ability to withstand severe stress (Ong and Pazarbasioglu 2014, Bernanke 2013).

Second, microprudential stress tests help financial institutions to improve their own risk-management. By forcing them to assess their resilience to a variety of novel scenarios, stress tests require banks to take a holistic look at their own risk-management practices (Bookstaber, Cetina, Feldberg, Flood and Glasserman 2014). As a consequence, more banks are now also engaged in serious internal stress tests (Wackerbeck, Crijns and Karsten 2016).

Third, microprudential stress tests have proven to be an effective mechanism to recapitalize banks (Armour, Awrey, Enriques, Gordon, Mayer and Payne 2016). In the EU, the stress tests have forced banks to raise their capital by 260 billion euros from 2011 to 2016 (Arnold and Jenkins 2016), and in the US the risk-weighted regulatory ratio of the banks that participated in the stress test went up from 5,6 procent at the end of 2008 to 11,3 at the end of 2012 (Bernanke 2013). Against a backdrop of frequent questions about the adequacy of banks' capital buffers[14], in part due to the gaming of risk weights (Behn, Haselmann and Vig 2016, Fender and Lewrick 2015, Groendahl 2015), many regulators have welcomed the role that stress tests have played to enhance the resilience of banks. Even if microprudential stress tests are not, strictly speaking, designed to assess and evaluate systemic risk, their role in raising capital adequacy standards can have the effect of enhancing resilience (Greenwood, Landier and Thesmar 2015).

Despite their strengths in specific areas, the current microprudential stress tests have been criticized on at least four grounds. First, and most importantly from the perspective of this chapter, microprudential stress tests ignore the fact that economies are complex systems (see, 1) and therefore are ill-suited to capture systemic risk. As discussed in section 3 and 4 of this chapter,

[14] See, for example, Admati and Hellwig (2014).

systemic risk materializes due to interconnections between heterogeneous agents (for example, in terms of leverage). By considering institutions in isolation, ignoring the interconnections and interactions between financial institutions that serve to propagate and amplify distress, the losses that result from adverse scenarios are substantially underestimated (Bookstaber, Paddrik and Tivnan 2014). Bernanke (2015), for example, describes describes that the majority of the losses in the last financial crisis can be traced back to such interactions as opposed to the initial shock emerging from credit losses in subprime mortgage loans.

Second, microprudential stress tests tend to impose an unrealistically large initial shock. Because regulators are aware of the fact that a microprudential modelling strategy does not capture the higher order losses on the balance sheets of individual financial institutions, they use a more severe initial scenario that causes direct losses to compensate for that. To generate a sufficiently large initial shock the scenario tends to depart quite strongly from reality. Often, the initial scenario posits a substantial increase in the unemployment rate as well as a sharp drop in GDP.[15] In reality, however, it is uncommon these conditions to precede a financial crisis, so the stress test might be testing for the wrong type of scenario.[16] Imposing an unrealistic shock – and not including higher order effects – can also affect the outcome of the stress test in unexpected ways. In particular, while stress tests with large initial shocks might get the overall losses right, they might fail to accurately capture the distribution of losses across institutions which ultimately determines which banks survive and which do not. For an investigation of this issue see for example Cont and Schaanning (2014).

Third, the value of the information produced by microprudential stress tests is increasingly being questioned. The outcomes of stress tests have converged (Glasserman, Tangirala et al. 2015), perhaps because banks seem increasingly able to "adapt to the test". This has left some to wonder what the information produced by the stress tests is actually worth (Hirtle, Kovner and Zeller 2016), and others to find that the value of such information is declining over time (Candelon and Sy 2015). Such concerns have been further fuelled by the apparent willingness of some regulators to allow banks to pass the test on the basis of dubious assumptions.[17]

Finally, the stress tests are commonly calibrated to the losses incurred during the last financial crisis, raising questions about their relevance in relation to current, let alone future, scenarios (Baptista, Farmer, Kleinnijenhuis, Wetzer and Williamson 2017) – not least because the financial system constantly changes.

5.3 Macroprudential Stress Tests

If the financial system is a complex system (see section 1), the whole is different from the sum of its parts (Farmer 2012). In other words, measures focused on the health of individual institutions

[15] See, for example, FED (2016), BoE (2016), ESRB (2016).

[16] Instead, exogenous shocks such as declining house prices or stock markets precede financial crises. These are commonly also part of the initial scenario.

[17] Deutsche bank, which has seen its share price fall significantly in 2016 on fears that it could face a US fine of up to 14bn was given a special treatment by the European Central Bank in the 2016 EBA stress tests, so that it could use the result of the stress test as evidence of it's healthy finances (Noonan, Binham and Shotter 2016).

(as microprudential stress tests would prescribe) will not necessarily guarantee the health of the financial system as a whole. In fact, such measures might destabilize the system Aymanns and Farmer (2015). To understand the system as a whole - and, by implication, systemic risk - stress tests have to account for feedback loops and non-linearities.

The inability of microprudential stress tests to appropriately account for systemic risk has prompted the development of a specific type of stress tests focused on this goal; the macroprudential stress test. Macroprudential stress tests aim to assess the resilience of the whole financial system, rather than that of one particular institution. To do that, they extend the microprudential stress test by including contagion effects between interconnected financial institutions that can arise following the initial adverse scenario. This means that the regulators must not only assess the effect of the initial shocks on the individual balance sheets, but must capture how the balance sheets are interlinked. They should also address what consequences such interlinkages have for the ability of financial distress to propagate throughout the system. The contagion models discussed in 4 can help inform regulators on how to model these higher order spill-over effects.

This section discusses two macroprudential models for banks, and one that combines banks and non-banks. The first two models, the Bank of England's "Risk Assessment Model of Systemic Institutions" (RAMSI) and the Bank of Canada's "MacroFinancial Risk Assessment Framework" (MFRAF), are used in stress tests. The last model, Office of Financial Research's (OFR's) "Agent-Based Model for Financial Vulnerabilities", is not.

5.3.1 Macroprudential Stress Tests of Banks

5.3.1.1 RAMSI Stress Test of the Bank of England

The Bank of England has pioneered the development and use of a macroprudential banking stress test, called the RAMSI model, to enhance its ability to assess the health of the UK's financial system and the financial institutions therein. The model evaluates how adverse shocks transmit through the balance sheets of banks and can cause further contagion effects (Burrows, Learmonth, McKeown and Williams 2012). It is based on earlier research that has been conducted by Bank of England researchers and others (Aikman, Alessandri, Eklund, Gai, Kapadia, Martin, Mora, Sterne and Willison 2009, Kapadia, Drehmann, Elliott and Sterne 2012, Alessandri, Gai, Kapadia, Mora, Puhr et al. 2009). The RAMSI stress test can be summarized as follows.

The stress test begins as a microprudential stress test. The effect on the balance sheet and profit and losses of banks projected following a set of adverse exogenous macro and financial shocks. Subsequently, possible feedback effects within the banking system are considered. If the initial shocks have caused a bank to fall below its regulatory capital ratio or have caused the bank to be shut out of all unsecured funding markets, the bank respectively suffers an insolvency or illiquidity default. Subsequently, the default causes two interbank contagion effects: firesale contagion and interbank contagion. The assets of the bank that are available for sale (AFS) are firesold. This causes mark-to-market (MtM) losses of the banks that hold the same assets. Banks that have interbank exposures to the defaulted bank suffer a credit losses. The combined effect of the MtM losses and the credit losses can cause other banks to default through insolvency or to default through illiquidity by being shut out of the funding market. If this happens the loop is repeated. If this does not happen, each bank's net operating expenses are invested in assets such that the bank targets its regulatory risk-weighted target ratio. The credit losses persist, but the MtM are assumed to disappear as each asset price returns to its fundamental value. Then, the next time step arises, and the process can be repeated starting with a balance sheet that includes the credit losses incurred in the previous time step. Thus, the RAMSI stress test turns a microprudential foundation into a macroprudential model by including interbank contagion effects, via firesales, interbank losses and funding liquidity contagion. Figure 8 displays what happens at each step of the RAMSI model. In what follows, the modelling approach used in each time step is described in more detail.

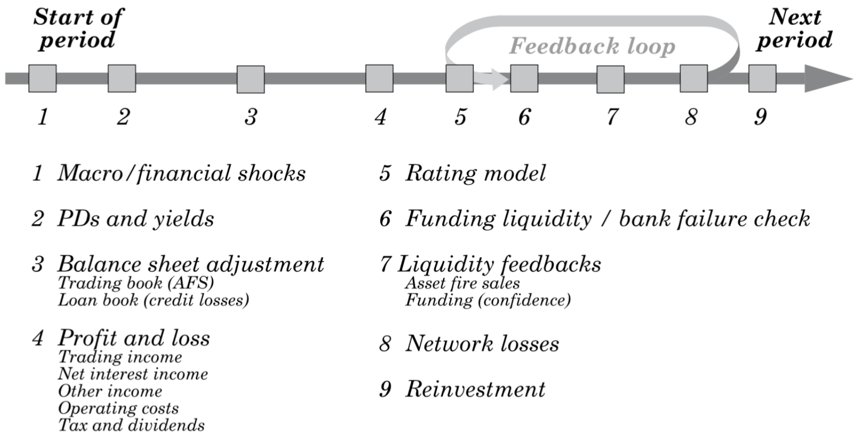


Figure 8: Description of the RAMSI stress test of the Bank of England. Source: Aikman et al. (2011).

The key inputs of the stress test are the composition of the initial balance sheets of banks, their interconnections, and the initial adverse exogenous shocks. The balance sheets are decomposed in 400 asset classes and 250 liability classes, and include various maturity buckets. The interbank exposures are estimated and common asset holdings stipulated. The evolution of the adverse macroeconomic and financial variables over the three-year time span of the stress test are determined with a large-scale Bayesian vector autoregression (BVAR). These variables are used as inputs in the stress test, and include levels and/or growth rates of real GDP, CPI inflation, real FTSE index, real house prices, government bond rates, unemployment, LIBOR spread and corporate bond spread.

A macroeconomic model then takes these variables as inputs to produce new variables, such as the post-stress yield curve, probability of default and loss given default, that are used to compute the factors that determine the first-round impact of the shock on the banks, via changes in a bank's balance sheet values, and profit and losses. These factors are: (i) credit risk; (ii) net interest income; (iii) noninterest (non-trading) income and operating expenses; and (iv) profit, taxes and dividends. The credit losses affect the bank's asset values and solvency position. The other factors effect the bank's profit and losses which ultimately feedback into a bank's solvency position.

Now that the direct impact of the adverse scenario on the balance sheet and the profit and losses (PL) is determined, the subsequent system-wide effects are considered. The first such affect is a funding liquidity shock. Based on the shocked balance sheets and PL, the credit score for the bank is computed, which the authors assume affects the funding cost of the bank and its ability to access the long-term and short-term funding market. This credit score takes into account liquidity and solvency characteristics of the bank's balance sheet, but also system-wide market distress. Examples include the maturity mismatch and asset liquidity, expected Tier I capital ratio, interbank market spread, and equity market fall. The greater the funding and or market liquidity, the greater the concerns about future solvency. The greater the wider market distress, the higher the credit score. If the credit score is above 25 points, a bank is assumed to be shut out of the long-term unsecured funding market. It can then try to replace its long-term unsecured funding with short-term unsecured funding, but this further deteriorates its credit score by increasing the maturity mismatch. If its credit score is above 35 points, the bank is shut out of the unsecured funding markets altogether (both long-term and short-term) and is assumed to default. Even if a bank is not shut out of a funding market, it can still experience an increase in its funding cost, which negatively affects its PL and thus increases its future vulnerability to shocks. The second such affect is a default, either due to insolvency following the direct effect of the credit shock on the balance sheet, or due to illiquidity following a loss of access to the funding market.

If a bank defaults two network contagion effects are considered: firesale contagion and interbank contagion. Upon default all of a bank's assets that were held as AFS are firesold. This causes the MtM value the assets of other banks who hold the assets that are firesold on their balance sheet to decrease, because the firesale causes a price impact. The price impact of the firesale is estimated using the following concave price impact function:

$$P_j^I = \max\{0, P_j[2 - \exp \phi \frac{S_{ij}}{M_j + \epsilon_j}]\}. \quad (2)$$

This equation shows that the price impact in asset class j of a firesale is larger if a bank i: sells more assets of j (ie S_{ij} is higher) and the market depth (which can be shocked in stressed periods by ϵ_j) is shallower (ie M_j is smaller). Upon a bank's default, other banks that have direct exposures to the defaulted bank suffer a loss given default (LGD) to their exposures that reflects a bankruptcy cost. The interbank losses are computed using the Eisenberg and Noe (2001) algorithm, as has been explained in section 4. If firesale losses or interbank losses cause a bank to default through insolvency or through being shut out of the funding market, the loop of network losses and balance sheet and funding liquidity updates is continued.

If no other bank defaults, the net operating income is computed, which is used to reinvest in assets to return to the bank's Tier I capital ratio (i.e. risk-weighted (RW) leverage) target. The net operating income is the difference between the operating income and operating expenses. The operating income consists of the interest income, noninterest income, and trading income. Depending on whether the net operating income is negative or positive a different rule is used to return to the RW-leverage target. The authors justify their assumption of RW-leverage targeting banks based on the observation that the RW-leverage of UK banks has been quite stable and based on research from Adrian and Shin (2010*b*) that shows that banks tend to do so (see, section 4). It should be noted that although bank's target a RW-leverage, they do not target a (unweighted) leverage ratio. As the initial scenario affects the PDs and thus the value of the Basel II RWs used in the RW-leverage calculation, targeting a constant RW-leverage means that bank's leverage can evolve in a pro-cyclical manner. This could lead to leverage cycles as discussed in section 3.

Finally, the reinvestment choice and incurred credit losses are used to update the balance sheet of each bank to start the next time step.

The results of the RAMSI model described in (Aikman, Alessandri, Eklund, Gai, Kapadia, Martin, Mora, Sterne and Willison 2009) have illustrated the role that funding liquidity contagion, firesales and exposure losses can play in driving banks to default who might have not defaulted if only the direct effect of the exogenous shock was taken into account. Using a macroprudential stress test, in other words, elucidates dynamics that would have gone unnoticed if only microprudential stress tests were used - as is to be expected in a complex system.

Three key findings illustrate this point. First, by looking at capital alone, the defaulting banks remain above the 4% regulatory minimum. But a combination of relatively mild solvency concerns, a weak liquidity position and elevated market interbank spreads is sufficient for wholesale depositors to withdraw funding, causing a bank default.

Second, the cumulative change in funding liquidity rating of banks that have defaulted has changed more than that on non-defaulted banks. This shows how a progressively worsening funding liquidity position can cause otherwise solvent financial institutions to default. Once a bank's funding liquidity position worsens its funding cost go up, decreasing its future profits. This in turn makes the bank more vulnerable to future shocks, which can again result in rising funding costs. This feedback loop of ever-worsening funding liquidity conditions can then drive a financial institution to default, while (other) healthy institutions that do not experience such a feedback loop remain alive.

Finally, the UK banking system's distribution of total assets is bimodal across simulations. In particular, they find that in most simulations the total asset value is high, but that in some simulations the total asset value is significantly lower. This shows that, once it materializes, contagion (i.e. fire sale and exposure contagion upon default, and funding liquidity contagion, see section 4) can have a significant negative impact on the total asset value in the system. In many cases the initial shock of the stress test does not cause significant losses and most banks remain healthy, but beyond a certain threshold these contagion effects are triggered and the total asset value is significantly reduced.

5.3.1.2 MFRAF Stress Test of the Bank of Canada

Contrary to the RAMSI model, the Bank of Canada's MacroFinancial Risk Assessment Framework (MFRAF) is at its core not a heterogeneous agent model but a global games model, such as those described in Morris and Shin (2001). In the way it sets up funding runs (i.e. as a global coordination game) it is similar to the seminal model of Diamond and Dybvig (1983) (discussed in 4. It captures three sources of risk that banks face (Anand, Bédard-Pagé and Traclet 2014, BoC 2014, 2012): solvency, liquidity, and spill-over risk (see Figure 9).

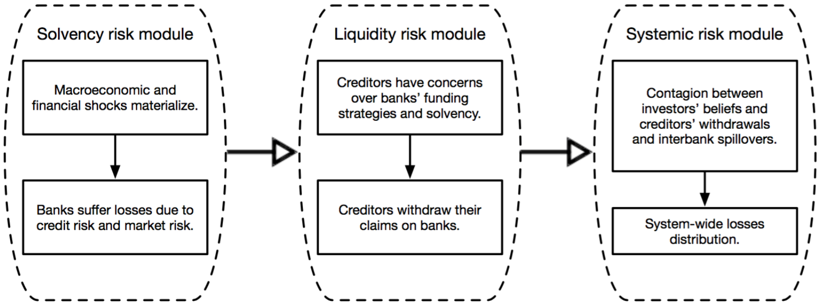


Figure 9: Description of the MFRAF stress test of the Canada. Source: Anand et al (2015).

The MFRAF stress test has been applied to the Financial Sector Stability Assessment (FSAP) of the Canadian financial sector conducted by the International Monetary Fund (IMF) in 2014 (IMF (2014)). The 2014 FSAP stress test, which considers the direct effects of adverse shocks on the solvency of banks, is microprudential. When extending it to capture system-wide effects (i.e. liquidity effects and spill-over effects) using MFRAF, overall losses to the capital of the Canadian banks rose with 20 percent. Again, it is clear that microprudential stress tests significantly underestimate system-wide losses. We will now discuss the theoretical underpinnings of the MFRAF stress tests, which builds on research at the Bank of Canada and elsewhere (Anand, Gauthier and Souissi 2015, Gauthier, Lehar and Souissi 2012, Gauthier, Souissi, Liu et al. 2014).

The theoretical model is described in Anand et al. (2015). The model captures how solvency risks, funding liquidity risks, and market risks of banks are intertwined. In essence, this works as follows: a coordination failure between a bank's creditors and adverse selection in the secondary market for the bank's assets interact, leading to a vicious cycle that can drive otherwise solvent banks to illiquidity. Investors' pessimism over the quality of a bank's assets reduces the bank's access to liquidity, which exacerbates the incidence of runs by creditors. This, in turn, makes investors more pessimistic, driving down other banks' access to liquidity. The model does not capture interbank contagion upon default, although this is captured in MFRAF (IMF 2014). We will now turn to the key equations in this model that describe the interaction between these various risks.

The model has three time periods, $t = 0, 1, 2$, and is populated by $N \in \mathbb{N}$ banks. A bank i's initial balance sheet consists of assets A_i and liabilities L_i and equity E_i. A bank i's assets consists of risky assets I_i and liquid assets M_i. The risky assets can be of high quality or low quality. Low quality assets are worth less than high quality assets $\phi_L < \phi_H$, and $\phi_H \in [0, 1)$. Although the bank knows the quality of the risky assets, the investors do not. Instead, they have a prior belief about the fraction of the risky assets that are of high quality, ω_t . This prior belief determines the price $\bar{\psi}$ that investors are willing to pay for the assets if the bank sells them. This price is referred to as the "pooling price", and is given by

$$\bar{\psi}_t = \omega_t \phi_H + (1 - \omega_t)\phi_L. \tag{3}$$

The pooling price determines the price discount that investors require on risky assets, and thus the price impact resulting from the sale of risky assets. The pooling price is endogenously updated in the model as investors update their beliefs about the quality of the risky assets. If a bank sells a part of its liquid assets, this causes no price impact.

The liability side of a bank's balance sheet consists of demandable debt D_i and equity E_i. The demandable debt is held by a pool of risk-neutral investors. The debt contract is issued at time $t = 0$. At time $t = 2$ the debt contract matures, and delivers a return of $1 + r_i$ if the bank has not defaulted, and otherwise returns nothing. At time $t = 1$ the investors can decide not to roll over the debt. In other words, they can decide to run. They will do this if they have concerns about a bank's solvency or liquidity position or fear that others will run.

We will now describe the evolution of the model over time, as depicted in Figure 10.

$t = 0$	$t = 1$ (round 1)	$t = 1$ (round 2)	$t = 2$
1. Debt issuance	1. Interim shock	1. Belief updated	1. Investment matures
2. Investments	2. Private signals	2. New pooling price	2. Final shock
	3. Debt withdrawals	3. New private signals	3. Debts honored
		4. Debt withdrawals	

Figure 10: Time steps in theoretical model of MFRAF stress test of the Bank of Canada. Source: Anand et al (2015).

At time $t = 0$ the banks issue debt D_i and creditors invest in this debt, $k \in [0, D_i]$. At time $t = 1$ each bank's assets are shocked with a S_i. A creditor k receives a noisy signal of the credit shock:

$$x_k = S_i + \epsilon_k, \tag{4}$$

where $\epsilon_k \sim U[-\epsilon, \epsilon]$. At time $t = 2$ each bank i will experience another credit shock L_i. Based on the expectation of a bank's solvency at time $t = 2$ conditional on the information known at time $t = 1$, assuming for now that there is no noise around the value of the credit shock at time $t = 1$, creditors take one of three actions: they always run, the never run, or they run with some probability. Creditors always run if given a bank i's current equity E_i and given the size of the shock that has materialized at time $t = 1$ S_i the bank is always insolvent at time $t = 2$, regardless of the size of the shock at time $t = 2$. Creditors never run if given a bank i's current equity E_i and given the size of the shock that has materialized at time $t = 1$ S_i the bank is always solvent at time $t = 2$ regardless of the size of the shock at time $t = 2$. Creditors run with some probability if depending on the size of the shock that materializes at time $t = 2$ and given the information known at time $t = 1$ the bank is either insolvent or solvent. Hence, conditional on the shock size at time $t = 1$ S_i the probability that bank i is insolvent at time $t = 2$ is given by:

$$Prob(E_i - S_i - L_i < 0) = \begin{cases} 1, & \text{if } S_i > E_i - \underline{L_i}, \\ 1 - G_i(E_i - S_i), & \text{if } S_i \in [E_i - \bar{L}_i, E_i - \underline{L_i}], \\ 0, & \text{if } S_i < E_i - \bar{L}_i, \end{cases}$$

where $L_i \in [\underline{L_i}, \bar{L}_i]$.

So without noise, there are three equilibria.

To resolve the multiplicity of equilibria, a global games refinement of Morris and Shin (2001) is considered. The model is embedded in an incomplete information setting, and each bank observes a noisy signal of the shock as discussed above. If the shock that a creditor observes x_k is above a critical threshold x_i^*, then creditor k withdraws funding from bank i. The illiquidity threshold is implicitly defined by the indifference condition for the expected payoff to a creditor between rolling over and withdrawing. It is increasing in the bank's equity, E_i, liquid assets, M_i, and returns, r_i, but is decreasing in its debt level, D_i. The illiquidity threshold is increasing in the investor's belief, ω, and the prices, ψ_H and ψ_L.

The comparative statistics make sense. If the bank's equity E_i increases, it has a larger buffer to absorb the credit shocks at time $t = 1$ and $t = 2$. Hence, creditors are less likely to withdraw because they judge the probability of insolvency of the bank at time $t = 2$ to be lower. If the bank's level of liquid assets M_i is larger, then the bank's ability to raise cash is greater, and the bank is more able to meet runs at the interim date. Therefore, the creditors are less likely to run. If the return r_i upon solvency increases, the creditors view it more favorable not to run and wait until time $t = 2$ instead, rather than to run at $t = 1$ and only obtain unity. If a bank has more debt D_i, it has relatively less access to liquidity to meet withdrawals. This incentivizes creditors to run sooner. The prior beliefs about the quality of the risky assets also affect the probability that creditors will run. If the investors' beliefs ω and prices ψ_H and ψ_L increase, the pooling price improves. This raises the ability of a bank to obtain cash to meet withdrawals, which in turn makes it less likely that creditors run in the first place.

Whether or not a bank defaults if a fraction of its creditors run, depends on the fraction of creditors that run l_i relative to the recourse to liquidity of the bank $\lambda_i(S_i; \bar{\psi})$. The recourse to liquidity of bank i is defined as

$$\lambda_i(S_i; \bar{\psi}) \equiv \frac{M_i + \bar{\psi}[Y_i - S_i]}{D_i}. \tag{5}$$

The bank's recourse to liquidity $\lambda_i(S_i; \bar{\psi})$ measures the fraction of depositors D_i that can at most be paid back (given the realised shock S_i and the pooling price $\bar{\psi}$). The numerator measures the maximum amount of cash the bank raises. It is equal to the sum of the liquid assets M_i and the cash value of the risky assets (post the shock S_i), which depends on the price investors are willing to pay (ie the pooling price $\bar{\psi}$). The denominator normalizes the numerator to arrive at the fraction of depositors that can at most be paid back.

If the fraction of depositors that run is greater than the fraction of depositors that can at most be paid back, bank i defaults. That is, the bank defaults at the intermediate time step if $l_i > \lambda_i(S_i; \bar{\psi})$. If banks default through illiquidity, the investors become more pessimistic. That is, ω goes down, and as a consequence the pooling price $\bar{\psi}$ falls. This reduces the banks' recourse to liquidity, which increases the probability that investors will run. If a run takes place, this makes investors more pessimistic again and further reduces the pooling price. This vicious cycle of self-fulfilling illiquidity between the investor updating the belief and the actions of bank creditors terminates once there is no additional information to be gained by the investor from observing the outcomes for banks.

Finally, at time $t = 2$, a second credit shock arrives. If this does not turn a bank insolvent, it will pay out its creditors the promised return on their investment.

This model is calibrated to the Canadian banking system, as explained in Anand et al. (2015).

The key results of the MFRAF stress test, described in BoC (2012), are that tail risk can be underestimated if contagion is not taken into account and that systemic risk is affected by the particular combination of the levels of three factors.

First, if the Canadian banking system's capital ratio is sufficiently low, the share of illiquid assets is sufficiently high, and the reliance of short-term funding sufficiently high, the tail of the loss distribution following a severe crisis scenario is significantly underestimated if the higher order liquidity risks and/or network spillover risks are not taken into account; only the initial credit losses of the severe scenario are captured. Figure 11 illustrates this results. However, the fat tail in the case with liquidity risks and/or network spillover risks completely disappears if the capital ratio is sufficiently high, the share of illiquid assets sufficiently low, and the reliance on short-term funding sufficiently small. This indicates that a highly leveraged financial system with many illiquid assets and much short-term funding is especially prone to contagion losses.

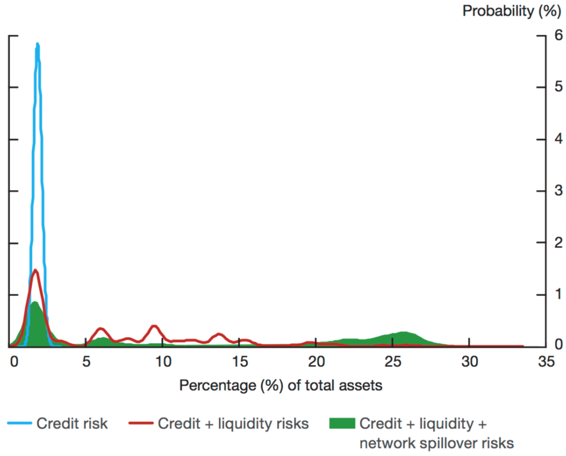


Figure 11: Loss distributions of a hypothetical banking system. The tail risk is underestimated if liquidity risks and/or network spill overs are not taken into account. Source: Bank of Canada Review (2012).

Second, the level of systemic risk, measured as the probability that at least one bank defaults, increases as the leverage of the banking system, illiquidity, and reliance on short-term funding increases (see figure 12). It shows that systemic risk kicks in much later if the leverage is lower. Only when the illiquidity is large and the short-term funding reliance is large will systemic risk materialize. But if systemic risk materializes, it kicks in as severely as in the case with a lower leverage.

Third, the positive relationship between systemic risk and reliance on short-term funding is much steeper when banks have fewer liquid-asset holdings, for both levels of capital. This means that an illiquid bank is more sensitive to disruptions in short-term funding markets. Similarly, the negative relationship between systemic risk and holdings of liquid assets is more significant when banks have a greater reliance on short-term funding.

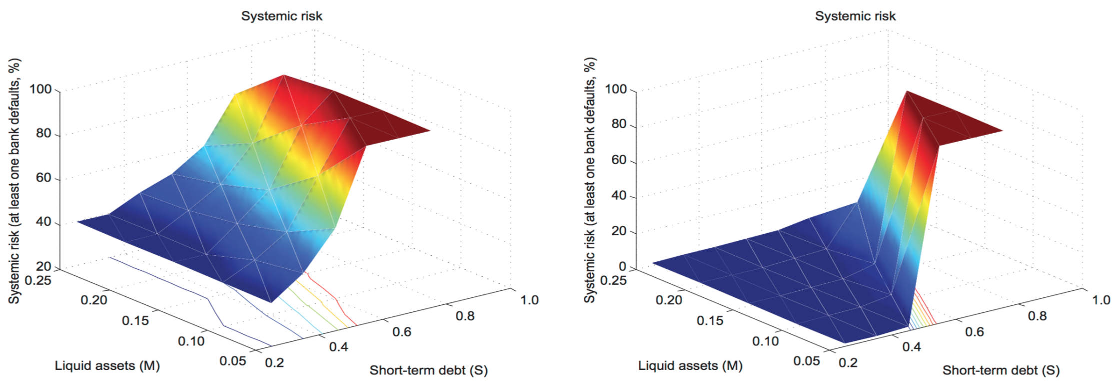


Figure 12: Systemic risk (measured as the probability of having at least one bank default) for different initial capital ratios (left panel: 6 procent; right panel: 8 procent) as a function of the fraction of liquid assets and the fraction of short-term funding, following an initial crisis shock. Source: Bank of Canada Review (2012).

5.3.2 Macroprudential Stress Tests of Banks and Non-Banks

5.3.2.1 ABM for Financial Vulnerabilities developed at the Office of Financial Research

The final system-wide stress testing model that will be discussed, the Agent-Based Model (ABM) for Financial Vulnerabilities (Bookstaber, Paddrik and Tivnan 2014), captures similar contagion mechanisms as MFRAF, but it does so using a different methodology. As it says on the tin, this is an agent-based model, designed to investigate the vulnerability of the financial system to asset- and funding-based firesales.

The financial system consists of banks that act as intermediaries between the cash provider (a representative agent for various types of funds) and the ultimate investors (i.e. the hedge funds). The hedge funds can receive funding from banks for long positions in return for collateral. The banks, in turn, receive funding from the cash provider in return for collateral. Funding and collateral therefore flow in opposite directions, as is illustrated in Figure 13.

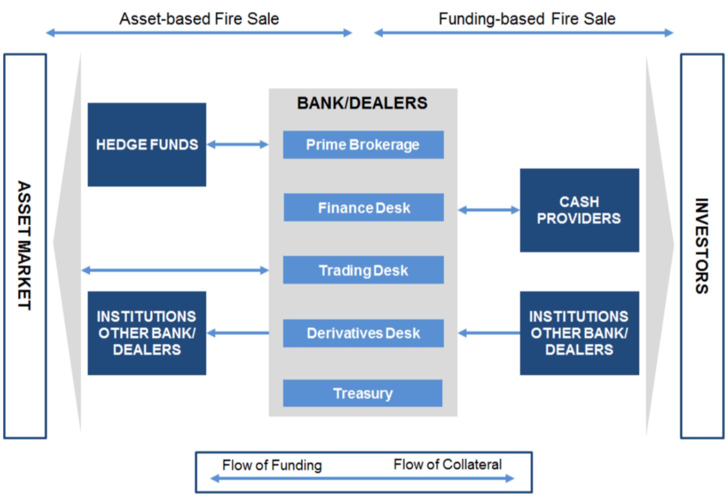


Figure 13: Map of the financial system and its flows, as considered in the ABM for Financial Vulnerabilities. Source: Bookstaber et al (2014).

Building on this detailed mapping of the transformations and dynamics of the financial system, the model explores contagion dynamics. It demonstrates that a stress test that only considers the direct effect of an adverse initial shock and not the higher order contagion effects, and excludes non-banks, would underestimate systemic risk. We now describe the model in greater detail, covering the model set up and the evolution of the prices, the cash provider, the hedge fund, and the bank.

Set up: The model consists of K banks, N hedge funds, one cash provider, and M asset markets.

Price formation: The evolution of the price of asset m is determined by

$$P_m(t+1) = \max\{0, P_m(t)(1 + R_m(t))\}. \tag{6}$$

Thus, the price floor is zero. The price in the next period $t+1$ updates relative to price at time t based on the return $R_m(t)$. The return is given by

$$R_m(t) = B_m Q_m^T(t) + R_m^R(t). \tag{7}$$

This formula expresses that the price shift occurs because of a random price move $C_m^R(t)$ and because of the price impact of the total net number of forced sales $B_m Q_m^T(t)$. This price impact in asset class m is a function of the price elasticity of demand B_m and the total quantity of forced sales by the banks and the hedge funds. That is,

$$Q_m^T(t) = \sum_{i=1}^{K} Q_{m,i}^{BD}(t) + \sum_{i=1}^{N} Q_{m,i}^{HF}(t). \tag{8}$$

Cash provider: The role of the cash provider c in the model is to provide secured funding to banks. The cash provider is a representative agent that represents financial institutions that typically provide funding to banks such as asset managers, pension funds, insurance companies, and security lenders, but most importantly, money market funds. Although the cash provider is not actively modelled, it can take two actions. First, it can set the haircut, and second it can pull funding from the banks. These actions affect the financial system in the following way. If the cash provider sets a higher haircut, this can force the hedge fund to engage in firesales (because the bank is assumed to pass on the haircut to the hedge fund). If the cash provider pulls funding from a bank, the bank needs to raise cash to pay back the secured loan. It can do so by pulling the funding from hedge funds, which may in turn force hedge funds to firesale. Alternatively, the bank firesales assets itself, if it cannot pull funding and has no cash.

The size of the loan the cash provider c extends to bank k depends on the amount of collateral the bank pledges, the haircut it receives, and the maximum amount of loan that the cash provider is willing to give to this bank. Thus, the amount of loan bank k receives at time t from cash provider c given that k has pledged a total amount of collateral equal to $C_k(t)$ is equal to

$$L_{c,k}(t) = \min\{L_{c,k}^{Max}(t), C_k(t)(1 - H_{c,k}(t))\}. \tag{9}$$

The haircut that the cash provider sets depends on the liquidity and solvency characteristics of the bank.

Hedge fund: Hedge funds are actively modelled. It has a balance sheet that consists of cash and tradable assets on the asset side, and secured loans and equity (and possibly short positions) on the liability side. A hedge fund funds its long positions in assets using funding from banks in the form of repo contracts. When funding themselves this way, hedge funds receive cash in return for collateral they pledge to the bank. A hedge fund achieves its short positions by borrowing securities from the bank against cash. Although the hedge fund does not face a regulatory leverage constraint, it faces an implicit leverage constraint based on the haircut it receives on its collateral. The haircut determines how much equity a hedge fund needs for a given amount of repo funding. If the haircuts on all types of collateral (i.e. on all types of assets that can be pledged as collateral) is the same, and assuming that the bank passes on the haircut it receives from the cash provider, the maximum leverage of the hedge fund n at time t is given by

$$\lambda_n^{Max}(t) = \frac{1}{H_{c,k}(t)}. \tag{10}$$

If the leverage of the hedge fund exceeds the maximum leverage, the hedge fund is forced to de-lever. It will do so by fire selling assets. This can cause MtM losses on other banks or hedge funds who hold the same assets. A hedge fund's leverage can exceed the maximum due to asset prices depreciations (as a consequence of firesales, for example) or increases in the haircut (due to the cash providers downward assessment of the bank's solvency and/or liquidity). If the hedge fund is forced to de-lever, it will attempt to go back to a "buffer leverage" level, which is below the maximum leverage value. If the hedge fund's leverage is below the maximum leverage, then it will increase or decrease its leverage to hit a "target leverage". Its actions to de-lever in such cases are assumed not to have a price impact, as these reflect day-to-day balance sheet adjustments which typically do not affect prices.

Bank Intermediaries The banks act as an intermediary between buyers and sellers of securities and between lenders and borrowers of funding. In its role, it facilitates maturity, liquidity, and risk transformations. The banks have various desks that play a role in these processes: the prime broker, the finance desk, the trading desk, the derivatives desk, and the treasury.

The various equations associated with the functioning of the bank dealer and its various subdesks can be found in Bookstaber, Paddrik and Tivnan (2014). On the whole, the bank can contribute to financial distress pre-default and post-default in various ways. Pre-default, the bank may have to fire sell assets or to pull funding from the hedge fund (which consequently may also have to engage in firesales) in order to raise cash, de-lever, or pay back funding to the cash provider (if the cash provider pulled its funding). In addition, by passing on an increased haircut to the hedge fund it can trigger a hedge fund to engage in firesales. Post-default, the bank contributes to exposure losses and further firesale losses.

The results of the ABM for Financial Vulnerability focus on the role of leverage, liquidity, and asset crowding in systemic risk, as well as on the evolution of contagion.

A key result concerns the forward-looking dynamic evolution of the value-at-risk (VaR) of the hedge fund's capital. It is found that the VaR in the forward simulation is very different depending on how far forward you simulate the model. The implication is that a portfolio investor's future estimate of the VaR depends on how long it wants to hold the portfolio. This value-at-risk is not dependent on the historical volatility of prices but on the forward-looking volatility of prices. This makes sense, because the future volatility of prices, especially following crisis shocks, does not have to be similar as the historical volatility of prices.

Another key result is that financial institutions that are not seemingly exposed to shocked assets can nonetheless experience losses. In this model, a hedge fund that receives an asset price shock might be forced to de-lever, thereby fireselling assets. If it does, it may firesell the asset that was shocked, but it can also firesell in other asset classes. In the latter case, financial insitutions that did not hold the initial shocked asset but do hold some of the other assets that are firesold experience asset price losses too. Potentially, this may force them to de-lever themselves, further passing on the shock.

This phenomenon can be described as common asset holding contagion. The degree and path of common asset holding contagion depends on the structure of the common asset holding network, in particular, on the level of crowding in certain asset classes.

5.3.3 Strengths and Weaknesses of the Current Macroprudential Stress Tests

Macroprudential stress tests are strongly complementary to microprudential stress tests, because they allow regulators to assess the resilience of the financial system rather than that of individual financial institutions. The current macroprudential stress tests have three related strengths

First, they provide insights into the interlinkages between financial institutions, mapping out how financial shocks transmit through individual balance sheets and affect other institutions. The data-driven methodology to establish the model setup (as well as the subsequent calibration) provide a promising avenue for future stress tests, but also for further data-driven research into the structure of the financial system (Aikman, Alessandri, Eklund, Gai, Kapadia, Martin, Mora, Sterne and Willison 2009).

Second, they capture the interactions between various financial institutions and contagion channels that can drive distress, and therefore capture (some of) the feedback effects that characterize the complex nature of the financial system. Especially the ABM for Financial Vulnerabilities makes an important contribution by including heterogeneous financial institutions, which is key to allow for emergent phenomena (Bookstaber 2017).

Third, in addition to capturing solvency risk, or separately investigating solvency and liquidity risk, the current macroprudential stress tests capture funding liquidity risk and the interactions between solvency and liquidity. The RAMSI model, for example, not only considers defaults through insolvency, but also through illiquidity, and takes their interaction into account. In case of the MFRAF, a particular strength is that market risk and funding liquidity are endogenously determined. Market risk is based on the degree of adverse selection. Because of asymmetric information, investors offer banks a pooling price for their assets. The pooling price (and hence the market liquidity) lowers if investors become more pessimistic and the quality of the assets is lower. Funding liquidity risk is determined as a function of the bank's credit and market losses (based on general market confidence, and thus a function of information contagion), its funding composition and maturity profile, and concerns that creditors may have over its future solvency.

Despite these strengths, there is substantial scope for improvement. First, most macroprudential stress tests only capture banks and its creditors, and therefore fail to capture interactions with non-banks that make up a substantial part of the financial system. Moreover, non-banks have played an important role in amplifying distress to the banking sector during the 2007-2009 financial crisis (Bernanke 2015). Therefore, failing to capture non-banks does not just exclude many institutions from the analysis, but also leaves regulators less well-equipped to understand the resilience of the subset of financial institutions they do study. The ABM for Financial Vulnerabilities is an exception, since it does include multiple types of financial institutions, but contrary to the RAMSI and the MFRAF models it is not used as a regulatory stress test.

Second, and relatedly, most macroprudential stress tests capture only a few types of interconnections, even though it is clear that the multiplicity of channels and interconnections between financial institutions play a critical role in spreading distress (Brunnermeier 2008). Notable examples of such contractual linkages include securitized products and credit default swaps.

Third, most current macroprudential stress tests only capture post-default contagion. However, in financial crises pre-default contagion is rampant, often resulting from actions that are prudent from a firm-specific risk-management perspective, but destabilizing from a system-wide perspective. A bank, for example, might engage in precautionary de-leveraging to avoid insolvency (i.e. breaking a leverage constraint), and this can add to further negative price spirals. Not capturing such dynamics implies that the total size of contagion, as well as the timing of contagion, is misunderstood.

These three areas of improvement essentially come down to the same point: the current macroprudential stress tests insufficiently capture the diversity of agents and interactions that make up the financial system, and therefore do not do justice to the complex nature of the financial system (or, for that matter, to the insights of the heterogeneous agent model literature, see sections 3 and 4). One of the important challenges is to device a modelling strategy that can capture these various effects, and the ABM for Financial Vulnerabilities offers a promising start; the model could easily be extended to capture more types of financial institutions (e.g. central clearing parties, pension funds), financial contracts (e.g. derivative contracts, securitized products), and constraints that drive behavior under stressed circumstances (Cetina, Lelyveld and Anand 2015). However, to fully realize its potential as a prototype for more advanced stress tests, the modelling framework should be further generalized and made more modular. We will now turn to a modelling framework that is designed to do just that.

6 The Future of Stress Testing is System-Wide

[18]So far, we have focused on the stress testing models that are currently being used. When thinking about what stress test models *should* look like, a starting point is to determine their purpose. The purpose we focus on in this section is to capture systemic risk. Such risk would not exist if firms existed in isolation, so adopting a system-wide perspective that takes account of interconnections and interactions is necessary. This view is increasingly shared amongst regulators and central bankers. Alex Brazier, head of financial stability at the Bank of England, recently emphasised that "the whole is different from the sum of the parts", and that tools are needed to take a system-wide perspective (Brazier 2017). This remark aligns with the observation made earlier that, if the financial system is a complex system, then the whole will be different than the parts. To understand the resilience of the financial system, microprudential stress tests are not sufficient, and macroprudential stress tests of banks and non-banks that better capture the diversity of actors and instruments in the financial system are necessary.

Our view is that such system-wide stress tests serve at least three important goals; to monitor financial stability, identify vulnerabilities in the financial system, and to evaluate policies designed to mitigate systemic risk. The first, monitoring financial stability, involves developing metrics that would allow regulators to see whether systemic risks are building up over time, and to have early-warning indicators to ensure that they can intervene in a timely manner.

The second, identifying vulnerabilities in the financial system, enables regulators to become aware of structural deficiencies in the financial system that render it vulnerable to systemic risk. Another way of phrasing the same point would be to say that it should identify sources of systemic risk, the factors that contribute to such risk, and the relative importance of those factors. Regulators should, on the basis of the stress tests, for example be able to analyze the network structure of the financial system (Acemoglu, Ozdaglar and Tahbaz-Salehi 2015, Caccioli, Shrestha, Moore and Farmer 2014, Cont, Moussa et al. 2010, Battiston, Puliga, Kaushik, Tasca and Caldarelli 2012, e Santos, Cont et al. 2010), evaluate asset-holding patterns and concentration risk, identify systemically important nodes (Battiston, Puliga, Kaushik, Tasca and Caldarelli 2012), and examine the maturity structure and leverage of a financial institution's balance sheet (Puhr, Santos, Schmieder, Neftci, Neudorfer, Schmitz and Hesse 2003, Hirtle and Lehnert 2014). Regulation or regulatory practice can also be the source of systemic-risk. For example, microprudential regulation that is meant to enhance the resilience of individual institutions can increase the fragility of the system in times of crisis when these requirements have procyclical effects (Aymanns and Farmer 2015, Danıelsson, Shin and Zigrand 2004).

The third, evaluating policies designed to mitigate systemic risk, touches on those latter concerns related to microprudential policies but include macroprudential policies as well. As noted, microprudential regulation may have undesirable procyclical effects. But it could also be the case that various regulatory instruments interact in ways that are undesirable from a system-wide perspective, or that macroprudential policies designed to make the whole system safer end

[18]This part of the paper is based on Baptista et al. (2017)

up doing the opposite. A system-wide stress testing model should be capable to study, at least qualitatively, such effects, and can therefore serve as a laboratory to run policy experiments.

Achieving these goals has proven challenging. Broadly speaking, there are two modeling strategies that could be pursued; microprudential stress tests could be made more macroprudential[19], or macroprudential stress tests are conducted in addition to microprudential stress tests and be developed on a stand-alone basis. We prefer the latter approach, because microprudential stress tests have value in terms of supervision and institution-specific risk management that is worth preserving in its own right.

If the macroprudential stress tests is going to capture the emergent phenomena that characterize the complex nature of the financial system, it has to be based on sufficiently granular data. To analyze how shocks propagate and to understand interacting effects, we need to have a clear sense of the connections between the financial institutions. When looking at the total aggregate exposures, as most current macroprudential stress tests do, measures of such interconnectedness will be too crude, making it difficult to assess how distress propagates. To understand how solvency and liquidity drive the dynamics of the system during normal times and in times of stress, we believe that macroprudential stress tests should be designed so that they can, when available, utilize data granular enough to capture individual contracts and legal entities (for examples of such datasets, see, BIS (2015*b*), Abad et al. (2016)).

In this section, we propose a blueprint for a new generation of macroprudential stress test (Baptista, Farmer, Kleinnijenhuis, Wetzer and Williamson 2017). This general framework provides the building blocks for developing bespoke system-wide stress test models. These building blocks – financial institutions, financial contracts, markets, constraints, information, and behavior – are discussed next.

6.1 A General Framework for System-Wide Stress Testing

6.1.1 Financial Institutions

Financial institutions sit at the heart of the financial system. In the literature, a common distinction is drawn between banks and non-banks. As discussed, including both in the same model is key to understanding systemic risk, since these sectors are of similar sizes in the US, UK and the EU (Burrows, Low and Cumming 2015, ECB 2015, FSB 2015) and are, in reality, highly intertwined (Adrian and Shin 2010*a*, Pozsar, Adrian, Ashcraft and Boesky 2010, Pozsar and Singh 2011, Mehrling, Pozsar, Sweeney and Neilson 2013, Pozsar 2013). Distress in the non-banking sector can easily propagate to the banking sector, and that is exactly what happened in 2008 (Kacperczyk and Schnabl 2010).

Despite these linkages being salient in reality, they are less so in systemic risk models or stress tests. As discussed, microprudential stress tests may have started out with banks alone, but

[19]RAMSI and MFRAF follow this approach; they model starts as a microprudential stress test, but then macroprudential elements were added on top

are now increasingly conducted on non-banks. The downside, however, of such microprudential stress tests is that they do not capture the critical interconnections between the various sectors. Such interconnections may not only increase the severity of the shocks, but can also completely change their dynamics. Microprudential stress tests of insurers or CCPs of the kind discussed above may therefore assess the individual resilience of these institutions, but will not say much about the contribution of such firms to systemic risk (either by originating or amplifying such risks), or whether such a firm is particularly vulnerable to distress coming from various types of interactions with other financial institutions.

To illustrate this point, the stress tests in ESMA (2015) might underestimate the vulnerability of a CCP and cannot assess the contribution to financial distress the CCP might cause upon its default, because it does not consider the (higher order) network effects of such a default. In addition, it might underestimate the vulnerability of the CCP to defaults elsewhere in the financial system. The model excludes the extra intra-financial system contagion losses that might hit the CCP default waterfall following the default of the largest two clearing members (CMs). Only the direct losses that the default of the largest two CMs might impose on the CCP are taken into account. Such losses stem from the CCP's losses on the derivative positions of these CMs that were not absorbed by the collateral the CMs posted. The contagion losses that the default of the largest two CMs might cause in the financial system, via financial contracts that are not cleared through the CCP, is not taken into account. If the ensuing contagion losses cause another CM of the CCP to default, this may impose extra losses to the CCP, which might cause the CCP to default.

Likewise, an insurer must be modelled in a system-wide stress test as part of the network. The EIOPA (2016) stress test does not fully capture the insurer's vulnerability to systemic risk as it does not capture the contagion losses (in addition to the initial losses) that might hit the insurer. It also insufficiently captures the insurer's contribution to systemic risk. For example, the Solvency II regulation might force insurers to react in a one-sided way to shocks (Baptista, Farmer, Kleinnijenhuis, Wetzer and Williamson 2017), thereby potentially contributing to the destabilization of markets. In conclusion financial institutions must be modelled as part of the financial network to accurately capture its vulnerability and contribution to contagion.

There are only few papers that have made (preliminary) attempts at capturing different types of financial institutions in one model. See, for example, Bookstaber, Paddrik and Tivnan (2014), Gennaioli et al. (2013).

6.1.2 Financial Contracts

Contracts populate the balance sheets of financial institutions, creating compositions of contracts unique to each. In stress testing models, these compositions of contracts are revalued in the face of shocks (usually as aggregates rather than individual contracts) to calculate an institution's new equity value. Moreover, contracts connect financial institutions in either direct or indirect ways. Direct interconnections include funding contracts between counterparties, whereas indirect interconnections can arise as a result of, for example, common asset holdings.

These interconnections can be useful in normal times, but under stressed circumstances they can act as carriers of contagion (Farmer, Kleinnijenhuis and Wetzer 2017).

We have already discussed in section 4 how the systemic risk literature has documented some of these interconnections, including interbank loans and common asset holdings. Some authors have covered interconnections through derivatives, in particular credit default swaps (CDSs) (Kaushik and Battiston 2013, Cont and Minca 2016, Markose, Giansante, Gatkowski and Shaghaghi 2010). However, most of these models only capture one financial contract type, and thus only one channel of contagion, which implies that the networks of interbank loans, asset holdings and CDSs are treated in isolation. As discussed in section 5.3.3, current macroprudential stress tests also only take a limited view of (interacting) contagion channels into account.

Casual empiricism reveals that such a view is at odds with events in the 2007-2009 financial crisis (Brunnermeier 2008). Papers that model the interactions between various contagion channels (which act over different types of financial contracts) support that view, and find that such interactions can amplify contagion (Kok and Montagna 2013, Caccioli, Farmer, Foti and Rockmore 2013). The macroprudential stress tests so far only capture some of the channels of contagion, but not all relevant ones, and do not always adequately capture the interaction between contagion channels. The Bank of England's RAMSI-model, for example, captures interbank contagion and firesale contagion (but only post-default), but not collateral contagion or CDS-contagion. The Bank of Canada's MFRAF model only captures three time-periods, and therefore fails to properly capture higher-order contagion at all. Bookstaber's model only captures secured funding and common asset holdings (Bookstaber, Paddrik and Tivnan 2014). Simultaneously including more contracts in the same model, as well as the interacting contagion effects they can host, is therefore a significant challenge for the field.

Box 2: Financial Institutions and Contracts Create a Bi-Partite Multiplex Network

Taken together, the financial institutions and the contracts that connect them form a *bi-partite multi-layered network* (Baptista, Farmer, Kleinnijenhuis, Wetzer and Williamson 2017) which, provided sufficient data is collected, regulators could construct with these two building blocks alone. The first set of *nodes* in such a network consists of financial institutions, which are directly connected through contracts (the *edges*), whereas the second set of nodes and indirect interconnections are made up of common asset holdings.

Having real time data, or even quarterly snapshots, of this network can be enormously valuable for regulators. First, simply the exercise of creating such a map of the financial system can be insightful. Such maps show how various institutions are connected to each other, and what their sizes and specializations are. Ideally, this should be known at a level that is more granular than aggregate exposures, so that the nature of the connections, and the role each institution plays within the wider system is clear too. But the basic point is that a simple map of the financial system allows a regulator to know what it regulates. An example of a map of the financial system that states something about the interconnections between financial institutions in the financial system is Pozsar et al. (2010).

Second, based on the structure of the multi-layered network, inferences can be made about the fragility of the financial system and about the factors contributing to this. Such measures are a priori measures of systemic risk based on the *static network*, without the need to model the evolution of the the network. For single-layered networks, typically of banks, research has demonstrated how to study the relationship between network structure and fragility. Acemoglu et al. (2015), for example, investigates how the fragility of the banking system depends on the *structure* of the interbank loan network. What is underinvestigated in the literature are papers that investigate how the joint structure of a multiple layers in a multi-layered network consisting of various types of financial institutions and financial contracts affect systemic risk.

The latter, determining the factors that contribute to systemic risk based on the static network, has also been studied. Various papers define *centrality* measures that can be used to identify systemically important financial institutions on the basis of their interconnected position in the network (Battiston, Puliga, Kaushik, Tasca and Caldarelli 2012). Others study how the composition of a network of overlapping portfolios affects systemic risk (Caccioli, Shrestha, Moore and Farmer 2014). Such papers study the robustness of networks as a function of diversification and concentration of asset holdings.

Third, up-to-date snapshots of the network can inform regulators about the direct effects of an initial shock. On this basis, regulators can assess the direct losses following the default of a particular institution, or the direct losses to financial institutions as a consequence of an asset shock. Such information could readily be used, for example to inform the decision to allow a financial institution to default, or the judgment whether to be concerned about price shocks to a particular asset class.

It is important to note that these networks do not require any modelling, and therefore do not generate modelling uncertainty. Adding the other building blocks (markets, constraints, information, and behavior) makes it possible to simulate the evolution of these networks.

6.1.3 Markets

Financial contracts are traded in markets. This is where prices are formed, new contracts are agreed upon, and existing contracts are modified and ended. Markets can take various forms, including that of an exchange or a dealer. Depending on the research question, markets can be modelled more or less realistically. Microprudential stress tests have so far not modelled markets at all, because they do not consider contagion effects. Macroprudential stress tests typically use a price-impact function (Burrows, Learmonth, McKeown and Williams 2012, Bookstaber, Paddrik and Tivnan 2014) as is the case in the systemic risk literature. Firesale models, for example, typically assume that price formation is affected by the net volume of sales via a price impact function (Caccioli, Farmer, Foti and Rockmore 2015, Caccioli, Shrestha, Moore and Farmer 2014, Cont and Schaanning 2014, Greenwood, Landier and Thesmar 2015, Duarte and Eisenbach 2015). A key challenge, which is especially relevant for modelling liquidity, is to include not just selling behavior but also buying behavior. For certain research questions, it might also make sense to model the formation of exchange-traded assets based on an order book (Bookstaber and Paddrik 2015).

6.1.4 Constraints

Financial institutions face constraints that they must meet, which limit their option set of available *eligible* actions. We consider four types of constraints; *regulatory* constraints, *contractual* constraints, *market* constraints, *and* constraints arising from *internal risk-limits*. Institutions face different sets of constraints, depending on their specific circumstances. For illustrative purposes, we can highlight various examples of such circumstances. Banks, for example, face leverage and liquidity regulatory constraints, but hedge funds usually do not. The contractual constraints that apply will depend on the composition of contracts an institution has on its balance sheet at a particular point in time. Not meeting these obligations will have repercussions, which can ultimately lead to default. Market constraints can imply particular expectations by investors, for example that banks maintain capital levels well above their regulatory requirements (Burrows, Learmonth, McKeown and Williams 2012). Not meeting such market expectations could trigger market runs (Anand, Gauthier and Souissi 2015). Finally, financial institutions could, in whole or in part, face internal risk limits that can include exposure limits to particular asset classes.

Constraints are important because they tend to drive the behavior of financial institutions in stressed periods and therefore determine the direction of contagion (Baptista, Farmer, Kleinnijenhuis, Wetzer and Williamson 2017). The extent to which they do depends on the degree to which they "bind"; the more binding the constraint, the more likely it will drive behavior in stress. It is not difficult to see why: breaching a binding constraint can trigger default (or trigger the firing of an individual trader breaching internal risk limits). It is not always clear whether constraints bind, and when. This can depend on many factors, including the market conditions, the type of institution and its role within the system, and the resources of supervisors and regulators.[20]

Current models do not capture this richness. Microprudential stress tests rely on (predominantly regulatory) constraints to assess whether institutions pass the adverse scenario. As we have seen, in the case of banks the key constraint is the regulatory capital ratio, and for insurers the asset-over-loan (AoL) ratio.

The literature has studied constraints and their impact on behavior in some detail. As discussed in section 3, Aymanns and Farmer (2015) have shown that the Basel II microprudential regulation that is meant to keep banks sufficiently well-capitalized causes leverage cycles. Adrian and Shin (2010*b*) found similar results. The notion that constraints can drive behavior of financial institutions (in stressed periods) and thereby cause contagion has also found support. Firesale models, including Greenwood et al. (2015) and Duarte and Eisenbach (2015), show that banks, who face a regulatory leverage constraint, can be forced to firesale in order not to breach regulatory limits. Cetina et al. (2015) show that, depending on what regulatory constraint binds, a bank responds differently to shocks and can trigger a different contagion channel. They show this for the different leverage and liquidity constraints that apply to banks (the leverage ratio, risk-weighted assets ratio, liquidity coverage ratio, and net stable funding ratio).

[20]Take as an example the liquidity coverage ratio. This liquidity constraint states that a bank must keep enough highly liquid assets to cover its net cash outflows over a thirty day period, in normal times. However, in times of stress, the regulator can loosen the requirement (Van Den End and Kruidhof 2013).

Bookstaber's macroprudential stress tests (Bookstaber, Paddrik and Tivnan 2014) makes clear that contractual constraints can drive the behavior of financial institutions in stressed periods too. In his model, the contractual constraints that drive behavior in stress are the requirement to meet margin calls and to pay back a loan if it is not rolled over.

Typically, the financial contagion models only capture a sub-set of the relevant constraints that drive behavior.

6.1.5 Information

Information plays an important role in the expectation formation by financial institutions about how certain key variables (such as asset prices, interest rates and real estate prices) of the future state of the financial system will evolve. These expectations in turn feed into the behavior of financial institutions, to (most optimally) act (to maximize profits and/or minimize losses) given the future expectation (and distribution) of the evolution of these variables.

Incorporating expectation formation is especially important when modelling aiming to model buying and selling behavior properly in macroprudential stress test.

For financial institutions to form a view of how asset prices and other relevant financial variables might evolve, they must have access to public information and information about their counterparties.

In the systemic risk literature since behavior is not properly modelled, information is certainly not yet considered. But if behavior will be more explicitly (assumed and modelled) information should come to play a role. Since behavior is not really part of a microprudential stress test information is typically not considered.

6.1.6 Behavior

Behavior is central to understanding systemic risk, but at the same time it is the most challenging part to model. Understanding the types of behavior that institutions may be forced into when under severe stress is key to modelling the dynamics that occur occur when risks start to crystalize. In our model, behavior means making decisions regarding the buying and selling of assets, as well as opening, continuing, or terminating contractual relationships (for example by choosing not to roll-over a funding relationship). Institutions can also choose not to honor contractual commitments, with the potential outcome that they default.

Constraints and information feed into behavior. At any point in time, whether under stressed circumstances or not, constraints will limit the set of available actions to a smaller set of eligible actions. In normal times, part of the behavior will be driven by the need to meet contractual obligations and avoid breaching internal risk limits. A margin call due to a small change in the collateral value must, for example, be met (unless the institution chooses to breach the constraint). In times of stress, however, the constraints in the model will be much tighter and bind more strongly, leaving the institution with less room to maneuver. Rather than just meet one constraint, an institution may simultaneously be forced to de-lever, meet a large margin call, and respond to the fact that interbank loans are no longer rolled over. In either case, expectations about future developments of the financial system will inform the course of action institutions take. This is where information comes in.

The model works in the following way. First, binding constraints will reduce the set of available actions to a (sub)set of eligible behavior. As long as an institution wants to avoid default, this latter subset provides the options out of which an action will be chosen. The second step, therefore, is to choose an action out of the set of eligible actions. Here, information and expectations, as well as some form of optimization, play important roles. What information a financial institution has access to, how it forms expectations, and what it optimizes is subject to modelling assumptions. For example, we can assume that a financial institution reduces assets proportionally to initial holdings, or sells its most liquid assets first. Such assumptions are common within the systemic risk literature.

Regardless of how the behavior is chosen from the eligible set, the results the models produce are explicitly conditional on these assumptions. The modelling framework does not ?hardcode? such assumptions, but leaves it to the user to decide. Some might find this a weakness of the methodological approach. But it also offers opportunities, for example the examine the impact of a variety of behavioral assumptions. Regulators can, for example, run parameter sweeps on the behavioral assumptions and assess what type of behavior results in the worst financial stability outcomes. It can then consider implementing regulation that discourages institutions to respond in this way.

Moreover, the strength of the framework must be evaluated against the alternatives. Microprudential stress tests do not capture behavior at all. The bank's reactions to initial adverse shocks, except in some cases the ability to retain dividends, are not considered (Constancio 2016). In the systemic risk literature, behavioral assumptions are made but not always explicitly. For example, firesale models usually assume that banks which are forced to de-lever do so by reducing their assets and liabilities as a vertical slice of their portfolio (Cont and Schaanning 2014, Greenwood, Landier and Thesmar 2015, Duarte and Eisenbach 2015). In reality, however, firms tend to exhibit clear preferences regarding what asset to sell first, for example their most liquid assets (Boyson, Helwege and Jindra 2011). Barring such examples, behavior in crisis is mostly driven by constraints, so if constraints do not bind institutions usually do not act – they only act to avoid breaching constraints. The macroprudential stress tests tend to follow the same approach.

Understanding behavior remains a key are for ongoing research and model development. In the meantime, the framework we propose is designed to give policymakers the flexibility to test different behavioral assumptions, and to consider the conditional outcomes and their sensitivity to these assumptions.

Box 3: Simulating the Evolution of the Network and Capturing Higher-Order Effects

Based on the information on *financial institutions* (primarily the composition of their balance sheet) and their interconnections via *financial contracts* , we can initialise the$t = 0$ multi-layered financial network (as has been explained in**Box 1**). If also the *markets* (market mechanism of matching buyers and sellers and setting prices), the *constraints* (which drive behaviour in stress), andbehaviour(which uses *information* as an input) are specified, we can simulate the *evolution* of the multi-layered network in stressed scenarios. This simulation will be explicitly conditional on the behavioural assumptions we adopt. Such simulations allow us to further explore contagion dynamics and inform measures of systemic risk. By running simulations, this setup can also be used as a 'laboratory' to run policy experiments or system-wide stress simulations and to evaluate existing policy.

6.2 Implementing Stress Testing Models in the General Framework

6.2.1 Flexible implementation of models depending on needs

Using the general stress testing framework's building blocks, bespoke system-wide stress testing models can be build. To be able to flexibly change the content of the platform, be able to separate parts of the model, and understand what is going on, the code that makes up the framework must be flexible, modular and transparent (Baptista, Farmer, Kleinnijenhuis, Wetzer and Williamson 2017).[21]

Depending on research or policy question of interest, and the data available, a different bespoke model might be implemented. For example, if one is interested in understanding – in a toy model setting – what the effect of trading strategies and key binding constraints applicable to key types of institutions is on price fragility, it might make sense to model within the box 'markets' an order book. Whereas, when the goal is to understand to common asset holdings contagion and its interaction with other types of contagion it might be sufficient to model price formation in the box 'markets' based on a price impact function. Or when the goal is to understand how vulnerable CCPs are to systemic risk and how much CCPs can contribute to systemic risk, it would be crucial to model in the box financial contracts' derivatives. Whereas, when one would like to understand how exposure risk, funding liquidity, and market liquidity risk interact, it might not immediately be necessary to model derivatives. When one would like to understand precisely how all the microprudential regulations on a bank (such as the various liquidity and leverage regulations) jointly affect systemic risk, it might make sense to model many of the key regulatory constraints in the 'constraints' box, but otherwise modelling the key leverage

[21] An example of a library that meets these criteria is the Economic Simulation Library (ESL). See website: https://economicsl.github.io. It is a community driven, open-source project to develop a user-friendly modeling library, both in Python and Java, for building agent-based (network) models of economic systems.

constraint might be sufficient. To investigate the key ways in which insurers contribute to systemic risk, it might not be necessary to model all other types of financial institutions within the 'financial institution' box . But when a central bank might want to gain a comprehensive understanding of the current systemic risk in the financial system, it might make sense to model all relevant financial institutions and all relevant financial contracts.

Whether a layer in the financial network will be modelled at the level of financial contracts or less granularly will depend on the data availability.

7 Conclusion

Computational models provide a useful complement to more traditional equilibrium based methods. They have already been shown to be essential for understanding the dynamics of systemic risk and for investigating the network properties of the financial system. Their role is likely to become even more important in the future as increasingly comprehensive fine-grained data becomes available, making it possible to carefully calibrate such models so that they can yield more quantitative conclusions. Due to the inherent complexity of the financial system, and in particular its nonlinear feedback loops, analytic methods are unlikely to be sufficient. We expect that computational methods will soon begin to go beyond hard wired behavioral rules and move increasingly toward myopic optimization. Thus in the future such models may begin to be able to withstand the Lucas critique. Behavioral economists have documented more and more situations in which people are not fully rational, emphasizing the obvious point that realistic behavior lies somewhere between full rationality and zero intelligence. Computational models offer the possibility of implementing realistic levels of strategic behavior, while allowing one to model the complex institutional structure of the financial system. We think that computational models will play an expanding role for understanding financial stability and systemic risk.

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