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BANK OF ENGLAND

Liquidity Risk, Cash Flow Constraints, and Systemic Feedbacks

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This draft: 15 August 2010

Abstract

This paper models liquidity feedbacks in a quantitative model of systemic risk. The model incorporates a number of channels important in the recent financial crisis. As banks lose access to longer-term funding markets, their liabilities may become increasingly short-term, further undermining confidence. Stressed banks' defensive actions include liquidity hoarding and asset fire sales. This behaviour can trigger funding problems at other banks and may ultimately cause them to fail. In presenting results, we analyse scenarios in which these channels of contagion operate, and conduct stochastic simulations to illustrate how liquidity feedbacks markedly amplify distress.

Key words: Systemic risk, financial stability models, funding liquidity risk, contagion.

***JEL* classification**: G01, G21, G32

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We are grateful to the following people who have provided valuable contributions and comments: David Aikman, Piergiorgio Alessandri, Niki Anderson, Richard Barwell, Emily Beau, Geoff Coppins, Jason Dowson, Bruno Eklund, Prasanna Gai, Harry Goodacre, Simon Hall, Andy Haldane, Elizabeth Martin, Emma Mattingley, Will Kerry, Nada Mora, Emma Murphy, Mikhail Oet, James Purchase and Matthew Willison. We would also like to thank seminar participants at the Bank of England and the NBER / Federal Reserve Bank of Cleveland Research Conference on "Quantifying Systemic Risk" (Boston, 6 November 2009) for helpful comments and suggestions.

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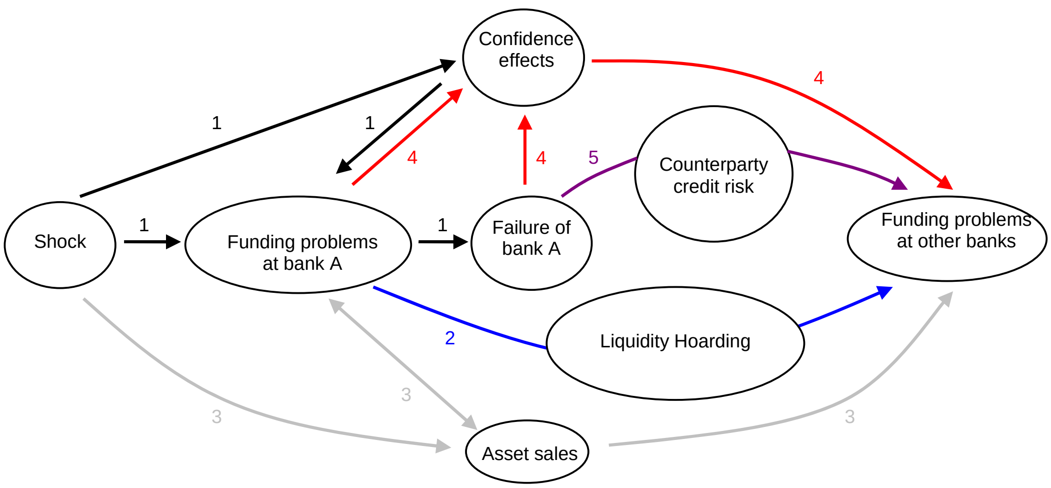
1 Introduction

The global financial crisis of 2007-09 served to reiterate the central role of liquidity risk in banking. Such a role has been understood at least since Bagehot (1873). This paper develops a framework that promotes an understanding of the triggers and system dynamics of liquidity risk during periods of financial instability and simulates the impact of these effects in a quantitative model of systemic risk.

The starting point of our analysis is the observation that although the failure of a financial institution may reflect solvency concerns, it invariably manifests itself through a crystallisation of funding liquidity risk. In a world with perfect information and perfect capital markets, banks would only fail if their underlying fundamentals rendered them insolvent. In such a world, examining the stock asset and liability position of a bank would be sufficient to assess its health, and solvent banks would always be able to finance random liquidity demands by borrowing, for example from other financial institutions. In reality, informational frictions exist and capital markets are not perfect. Hence, a bank may find it difficult to obtain funding if there are concerns about its solvency, regardless of whether or not those concerns are substantiated. In such funding crises, the stock solvency constraint no longer fully determines the survival of the bank; what matters is whether the bank has sufficient cash inflows, including income from asset sales and new borrowing, to cover all cash outflows. In other words, the bank's cash flow constraint becomes critical.

The cash flow constraint also makes it also possible to assess how banks' defensive actions during a funding liquidity crisis may affect the rest of the financial system. Figure 1 provides a stylised overview of the transmission mechanisms. For simplicity, it is assumed that the crisis starts with a deterioration in the solvency position of one bank. This undermines confidence and leads to liquidity problems at this institution (channel 1 in Figure 1). In line with crisis dynamics, the bank is only likely to lose access to longer-term funding markets initially. But this can create a 'snowballing' effect, whereby the bank's funding position deteriorates as the amount of short-term liabilities which have to be refinanced in each period increases over time. In an attempt to stave off a liquidity crisis, the distressed bank takes defensive actions, which may in turn have a systemic impact (channels 2 and 3). Initially, it may hoard liquidity by shortening the maturities of the interbank market loans it provides. It may also cut the provision of interbank market loans completely. Both these actions could create or intensify the funding problems at other banks that were relying on the distressed bank for funding (channel 2). The bank could also sell assets, which could depress market prices, potentially causing distress at other banks because of mark-to-market accounting or increased collateral calls (channel 3). In addition, funding problems could also spread via confidence effects (channel 4) and, in the event of a bank failure, via counterparty credit risk (channel 5).

Figure 1: Funding Crises in a System-Wide Context

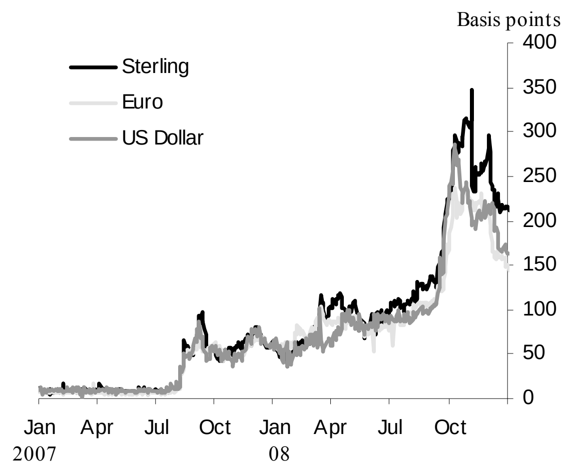


The main innovation of this paper is to provide a quantitative framework showing how shocks to fundamentals may interact with funding liquidity risk and potentially generate contagion which can spread across the financial system. Ideally, we would be able to assess liquidity crises empirically using a calibrated general equilibrium model. This would account for the optimal response of all players to particular shocks in a framework incorporating banks' cash flow constraints. But such a model does not exist and is likely to prove very hard to develop given the difficulties of introducing banks and generating non-linear crisis dynamics in general equilibrium models. Therefore we rely on plausible rules of thumbs, based on a range of sources, including behaviour observed in past crises, including the most recent one. This carries the advantage that it provides for a flexible framework which can capture a broad range of features and contagion channels of interest. This flexibility helps to make the model relevant for policy making, as it can provide a benchmark for assessing overall systemic risk given a range of solvency and liquidity shocks.

Our modelling approach disentangles the problem into several steps. First, we introduce a 'danger zone' approach to model how shocks affect individual banks' funding liquidity risk and how problems may amplify due to ‘snowballing’ effects. The danger zone approach is simple and transparent (yet subjective) as we assume that certain funding markets close if banks solvency and liquidity conditions – as summarised by a danger zone score – cross particular thresholds. We adopt this stylised approach towards modelling the closure of funding markets as the stochastic nature of the cash flow constraint cannot be properly estimated because of the binary, non-linear nature of liquidity risk, and because liquidity crises in developed countries have been (until recently) rare events, so data are extremely limited. Second, we combine the ‘danger zone’ approach with behavioural reactions, some of which are driven by banks’ cash flow constraints, to assess how liquidity crises can spread through the system. In particular, we demonstrate how liquidity hoarding and asset fire sales may improve the hoarding / selling bank’s liquidity position but worsen the liquidity position of other banks. Last, using the ‘RAMSI’ model presented in Aikman *et al* (2009), we simulate sequences of macroeconomic shocks over time to generate a distribution for bank profitability which allows us to assess how these shocks can interact with funding liquidity risk in a system-wide context and exacerbate overall systemic risk.

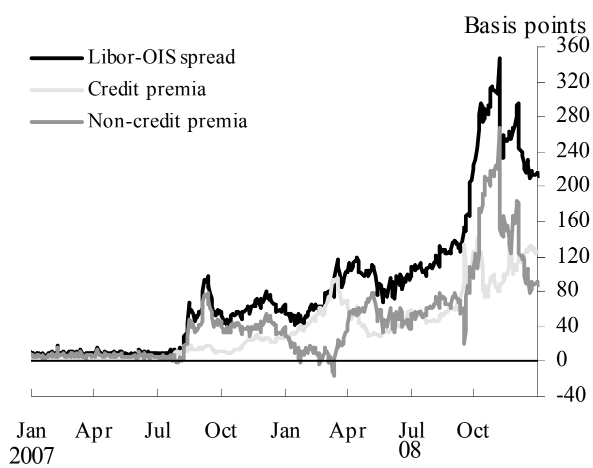
The feedback mechanisms that we have embedded in the model all played an important role in the recent and/or past financial crises. For example, the deterioration in liquidity positions associated with ‘snowballing’ effects was evident in Japan in the 1990s (see Figures 14 and 15 in Nakaso (2001)). And in the recent crisis, interbank lending collapsed from very early on with spreads between interbank rates for term lending and expected policy rates in the major funding markets rising sharply in August 2007, before spiking in September 2008 following the collapse of Lehman Brothers (Figure 2). Throughout this period, banks stopped lending to each other at all but the shortest maturities, with institutions forced to roll over increasingly large portions of their balance sheet at very short maturities. The quantity of interbank lending also declined dramatically and there was an unprecedented increase in the amounts placed by banks as reserves at the major central banks. It is hard to disentangle empirically the relative importance of counterparty credit risk and banks’ concerns about their own future liquidity needs in explaining the interbank market collapse. But anecdotal evidence suggests that, at least early in the crisis, banks were hoarding liquidity as a precautionary measure so that cash was available to finance liquidity lines to off-balance sheet vehicles that they were committed to rescuing, or as an endogenous response to liquidity hoarding by other market participans. Figure 3, which decomposes the interbank spread in the sterling, US dollar, and euro markets into contributions from credit premia and non-credit premia, and recent empirical work Acharya and Merrouche (2009) and Christensen et al (2009), all lend support to this view.

Figure 2: Twelve-month Interbank Rates Relative to Expected Policy Rates[(a)]



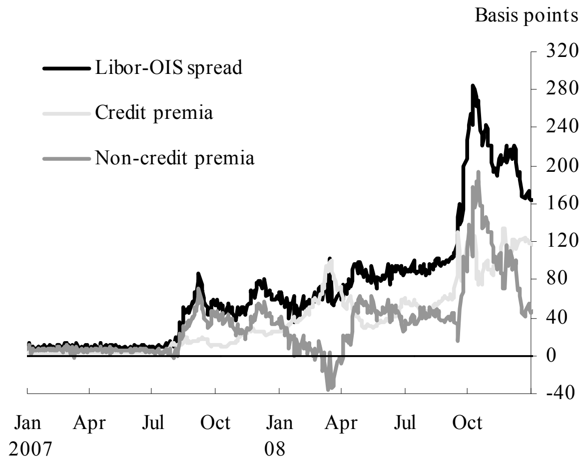
Sources: British Bankers' Association, Bloomberg and Bank of England calculations.
(a) Spread of twelve-month Libor to twelve-month overnight index swap (OIS) rates.

Figure 3(a): Decomposition of the Sterling 12-month Interbank Spread[(a)(b)]



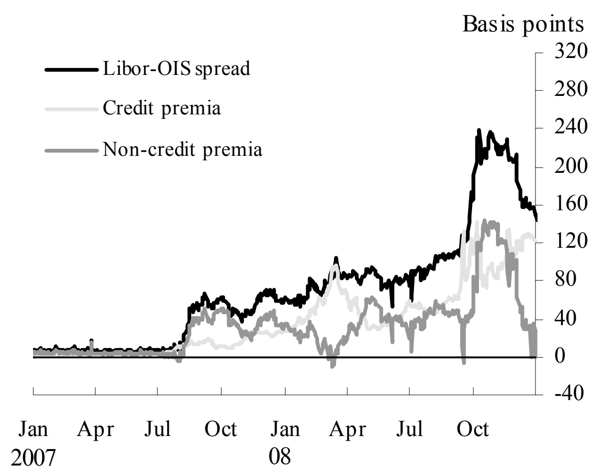
Sources: British Bankers' Association, Bloomberg, Markit Group Limited and Bank of England calculations.
(a) Spread of twelve-month Libor to twelve-month overnight index swap (OIS) rates.
(b) Estimates of credit premia are derived from credit default swaps on banks in the Libor panel. Estimates of non-credit premia are derived by the residual. For further details on the methodology, see Bank of England (2007, pp. 498-499).

Figure 3(b): Decomposition of the Dollar 12-month Interbank Spread [(a)(b)]



Sources: British Bankers' Association, Bloomberg, Markit Group Limited and Bank of England calculations.
(a) Spread of twelve-month Libor to twelve-month overnight index swap (OIS) rates.
(b) Estimates of credit premia are derived from credit default swaps on banks in the Libor panel. Estimates of non-credit premia are derived by the residual. For further details on the methodology, see Bank of England (2007, pp. 498-499).

Figure 3(c): Euro Decomposition of the Euro 12-month Interbank Spread [(a)(b)]



Sources: British Bankers' Association, Bloomberg, Markit Group Limited and Bank of England calculations.
(a) Spread of twelve-month Libor to twelve-month overnight index swap (OIS) rates.
(b) Estimates of credit premia are derived from credit default swaps on banks in the Libor panel. Estimates of non-credit premia are derived by the residual. For further details on the methodology, see Bank of England (2007, pp. 498-499).

It is also clear that the reduction in asset prices after August 2007 interacted with mark-to-market accounting to intensify funding problems in the system, particularly for those institutions reliant on the repo market who were forced to post more collateral to retain the same level of funding. Whilst it is hard to identify the direct role of fire sales in contributing to the reduction in asset prices, it is evident that many assets were carrying a very large liquidity discount.

Finally, confidence contagion and counterparty credit losses came to the fore following the failure of Lehman Brothers. The former was evident in the severe difficulties experienced by the other US securities houses in the following days, including those which had previously been regarded as relatively safe. And counterparty losses also contributed to the systemic impact of its failure, with the fear of a further round of such losses via credit derivative contracts being one of the reasons for the subsequent rescue of American International Group (AIG).

There have been several important contributions in the theoretical literature analysing how liquidity risk can affect banking systems, some of which we refer to when discussing the cash flow constraint in more detail in section 2. But empirical papers in this area are rare. One of the few is van den End (2008), who simulates the effect of funding and market liquidity risk for the Dutch banking system. The model builds on banks' own liquidity risk models, integrates them to system-wide level and then allows for banks' reactions, as prescribed by rules of thumb. But the paper only analyses shocks to fundamentals and therefore cannot speak to overall systemic risk.

Measuring systemic risk more broadly is in its infancy, in particular if information from banks' balance sheets is used (Borio and Drehmann, 2009). OeNB (2006) and Elsinger *et al* (2006) integrated balance-sheet based models of credit and market risk with a network model to evaluate the probability of bank default. Alessandri *et al* (2009) introduced RAMSI and Aikman *et al* (2009) further extend the approach in a number of dimensions. RAMSI is a comprehensive balance-sheet model for the largest UK banks, which models the different items on banks' income statement (via modules covering macro-credit risk, net interest income, non-interest income, and operating expenses), and integrates feedback effects between banks. Aikman *et al* (2009) also incorporate a simplified version of the 'danger zone' framework developed more fully in this paper. But in their framework, contagion can only occur upon bank failure due to confidence contagion, default in the network of interbank exposures (counterparty risk), or from fire sales which are assumed to depress asset prices at the point of default. In particular, they do not incorporate banks' cash flow constraints and do not allow for behavioural reactions such as ‘snowballing’ effects, liquidity hoarding or pre-default fire sales, all of which are key to understanding the systemic implications of funding liquidity crises.

The paper is structured as follows. Section 2 provides the conceptual and theoretical framework for our analysis, focusing on the potential triggers and systemic implications of funding liquidity crises through the lens of the bank’s cash flow constraint. Sections 3 and 4 focus on our quantitative modelling – section 3 provides details on how the danger zone approach captures the closure of funding markets to individual institutions; section 4 presents details and partial simulation results of how behavioural reactions and the danger zone approach interact to create systemic feedbacks. Section 5 provides a high level overview over RAMSI, which is used to model shocks to fundamentals. Section 6 presents full model simulation results which identify the contribution of funding liquidity risk and systemic liquidity feedbacks to the projected outcomes for the banking system, and section 7 concludes.

2 Funding Liquidity Risk in a System-Wide Context: Conceptual and Theoretical Issues

2.1 The Cash flow constraint

Liquidity risk arises because revenues and outlays are not synchronised (Holmström and Tirole (1998)). This would not matter if agents could issue financial contracts to third parties, pledging their future income as collateral. Given asymmetric information and other frictions, this is not always possible in reality. Hence, the timing of cash in- and out-flows is the crucial driver for funding liquidity risk and a bank is liquid if it is able to settle all obligations with immediacy (see Drehmann and Nikolaou (2009)).[1] This is the case if , in every period, cash outflows are smaller than cash inflows, along with the stock of cash held and any cash raised by selling assets (or repoing those assets), or

$$\begin{gathered} \textit{Liabilities}_{(Due)} + \textit{Assets}_{(New/Rolled\ over)} \\ \leq \\ \textit{Net Income} + \textit{Liabilities}_{(New/Rolled\ over)} + \textit{Assets}_{(Due)} + \textit{Value of Assets Sold Repoed.} \end{gathered}$$

Breaking down these components further:

$$\begin{gathered} WL_{Due} + RL_{Due} + WA_{New,Ro} + RA_{New,Ro} \\ \leq \\ \textit{Net Income} + WL_{New,Ro} + RL_{New,Ro} + WA_{Due} + RA_{Due} + LA^S + \Sigma p_i * ILA_i^S, \end{gathered} \tag{1}$$

[1] Drehmann and Nikolau (2009) discuss how this definition of funding liquidity risk relates to other definitions commonly used.

where:

- $WL(A)$ are wholesale liabilities (assets),
- $RL(A)$ are retail liabilities (assets),
- LA^S are the proceeds from the sale of liquid assets such as cash or government bonds,
- ILA_i^S is the volume of illiquid asset i sold or used as collateral to obtain secured (repo) funding,
- p_i is the market price of illiquid asset i, which may be below its fair value and possibly even zero in the short run.
- Subscripts $_{Due}$, $_{New}$ and $_{Ro}$ refer to obligations which are contractually due, newly issued or bought, and rolled over respectively.

We note several issues. First, the flow constraint is written in terms of *contractual* maturities as these are the ultimate drivers of funding liquidity risk in crises. But the constraint can also incorporate behavioural maturities which are different from the contractual ones by equating certain due payments (*eg* RL_{Due}) one-for-one with rolled over payments (*eg* RL_{Ro}). For example, many retail deposits are available on demand. In normal conditions, a bank can expect the majority of these 'loans' to be rolled over continuously and hence the behavioural maturity is much higher. But, in times of stress, depositors may choose to withdraw, so the behavioural maturity may collapse to the contractual one.

Second, equation (1) still provides a high level view of the flow constraint. For example, contingent claims are an important driver of funding liquidity risk. In particular firms rely heavily on credit lines (see, for example, Campello *et al* (2009)). Equally, banks negotiate contingent credit lines with other banks. We do not include off-balance sheet items separately, because once drawn they are part of new wholesale or retail assets or liabilities. Repo transactions are an important component of banks' liquidity risk management. Even though technically different, we treat them as part of the asset sales category because in both cases, the market price determines the value that can be raised from the underlying illiquid asset. Transactions with the central bank are also included in this category. These occur regularly, even in normal conditions as banks obtain liquidity directly from the central bank during open market operations.[2]

[2] Consistent with the rest of RAMSI, we assume that there is no extraordinary policy intervention in crises, so the cash flow constraint presumes that there is no intervention to widen central bank liquidity provision in a way which would allow banks to obtain more cash from the central bank than they could obtain through asset sales or repo transactions in the market.

Beyond this, different funding markets split into several sub-markets such as interbank borrowing, unsecured bonds, securitisations, commercial paper for interbank markets etc. And there is also clearly a distinction between foreign and domestic funding markets. These separate markets may have quite different characteristics that make them more or less susceptible to illiquidity. There are too many factors relevant to funding market dynamics to incorporate them all in a model of systemic risk. But there are two that we judge to be sufficiently important to split them out separately. First, we differentiate between secured and unsecured markets. And second, we split unsecured funding into longer-term and shorter-term markets. We discuss these in more detail later in the paper.

Finally, note that ex-post liquidity outflows will always equal inflows. If the bank is unable to satisfy the flow constraint, it will become illiquid and default. Conversely, if the bank has excess liquidity, it can sell it to the market, for example as WA_{New}. In the extreme, it will deposit it at the central bank but such reserves will generally be remunerated below the market interest rate. Ex-ante, however, banks are uncertain whether the flow constraint will be satisfied in all periods, ie they face funding liquidity risk. The right-hand side of equation (1) shows that this risk is driven by banks' ability to raise liquidity from different sources. The possibilities and implications of different choices are discussed in detail below. Before doing so, it is important to highlight a simple fact that is clear from equation (1): funding liquidity risk is driven by the amount of liquidity the bank needs to raise to be able to pay out all maturing liabilities and fund new assets. Hence, the mismatch between (contractually) maturing liabilities and assets is a key driver for funding liquidity risk. It follows that, ceteris paribus, a bank with a larger share of short term liabilities faces greater funding liquidity risk.

2.2 The trigger for funding problems at individual institutions

Under normal business conditions, banks are able to meet their cash flow constraints in every period, as they will always be able to obtain new wholesale funding or sell assets in a liquid market. But this may not be the case in a crisis. To understand crisis dynamics better, we first discuss the trigger events for funding problems at an individual institution before analysing how funding crises can spread through the system. Much of the theoretical literature on funding liquidity risk is focussed around modelling the former.

Most theoretical models can be cast in terms of the flow constraint. For example, Diamond and Dybvig (1983) assume there is only one illiquid investment project ILA_i which pays a high, certain payoff in period 2 but a low payoff p_i if liquidated early in period 1 (the high period 2 return guarantees that the bank is always solvent). The bank is entirely funded by demand deposits (RL_{Due}). It is known that a fraction of (*early)* depositors only care about consumption in period 1, while other *(late)* agents (which cannot be distinguished by the bank) are patient and prepared to wait until period 2, though they can withdraw in period 1 if they wish. To satisfy withdrawals of early depositors, the bank invests a fraction of its deposits into liquid assets LA^S. For simplicity, the bank has to pay no costs and interest payments are subsumed into liabilities to depositors, ie *net income = 0.* Given that all other terms in the cash flow constraint are also assumed to be zero, equation (1) in period 1 for the Diamond and Dybvig bank looks like:

$$RL_{Due}^{early} + RL_{Due}^{late} \leq RL_{Ro}^{late} + LA^S + p_i * ILA_i$$

Under normal circumstances, late depositors roll over their demand deposits ($RL_{Due}^{late} = RL_{Ro}^{late}$) and the bank can meet its cash flow constraint as the investment in the short term asset is sufficient to pay back early depositors. But if late depositors are unwilling to roll over and start a run on the bank ($RL_{Ro}^{late} = 0$), the bank is forced to start selling its illiquid assets at p_i, which is assumed to be below the fair value of the asset. Given that the bank is fundamentally sound, bank runs should not happen. But, as payoffs are low when all late depositors run, an equilibrium exists in which it is optimal for all agents to run. This generates the possibility of multiple equilibria, whereby fundamentals do not fully determine outcomes and confidence has an important role.

Even though very stylised and focused on a single bank, this model captures several key features of liquidity crises. First, contractual maturities matter in a liquidity crisis as the ‘behavioural’ maturities of late depositors collapse in stressed conditions from two periods to the contractual maturity of one period.

Second, funding and market liquidity are closely related. If the bank’s assets were liquid, so that p_i equalled its fair value, the bank could always sell assets to satisfy unexpected liquidity demands and would never be illiquid but solvent. As discussed in the introduction, to assess the riskiness of banks in this case, it would be sufficient to focus on the stock solvency constraint rather than look at a combination of stocks and flows.

Third, confidence and beliefs about the soundness of an institution and the behaviour of others play an important role in the crystallisation of funding liquidity risk. However, the result that bank runs are purely driven by sunspot equilibria is not particularly realistic: bank runs only tend to occur when there are strong (mostly justified) doubts about the fundamental solvency of a bank, or the bank has a very weak liquidity position. Chari and Jagannathan (1988) therefore introduce random returns and informed depositors in the model, which can induce bank runs driven by poor fundamentals. More recently, global game techniques have been applied to this problem (Rochet and Vives, 2004; Goldestein and Pauzner, 2005). Our empirical strategy is in the spirit of these papers: liquidity crises only tend to occur in our simulations when bank fundamentals are weak, even though it can still be the case that a bank is illiquid but solvent.

2.3 System dynamics of funding liquidity crises

The focus of our work is to capture the system-wide dynamics of liquidity crises. Figure 1 identified several channels through which a funding crisis at one bank could spread to the rest of the financial system. These can arise because banks react to a deterioration in their own funding position or other banks respond to the initial shock. In terms of the latter, confidence contagion may play an important role (channel 4 in Figure 1). This could be interpreted through fundamentals, whereby a liquidity crisis in one institution reveals some information on the likelihood of insolvency of other banks with similar investments (Chen, 1999).[3] Alternatively, confidence contagion could simply reflect panic, whereby investors decide to run on similar banks purely because of sentiment.

More generally, system confidence effects can contribute to systemic liquidity crises. Caballero and Krishnamurthy (2008) show that (Knightian) uncertainty may be triggered by a small shock, which is not necessarily a funding problem at one bank but could simply be a downgrade of an important marker player. Anticipating potential funding needs in the future, banks start to hoard liquidity. Liquidity hoarding by surplus banks may also be a result of asymmetric information

[3] Contagious bank runs can also affect the investment incentives of banks, making system-wide banking crisis even more likely (see Drehmann, 2002, and Acharya and Yorulmazer).

and heightened counterparty credit risk following some adverse shocks (Heider *et al* (2009)). This may even lead to a complete freeze of interbank markets.

In practice, banks may not stop interbank lending completely. As has been observed during the recent financial crisis, it may be the case that interbank market funds are available but only at very short maturities. This is advantageous to the lender as these short-term loans can be realised quickly and hence can be used as a buffer to potential liquidity shocks. In addition, the credit risk associated with short maturity loans is lower than that for long maturity loans.

The possible systemic consequences of liquidity hoarding linked to funding crises (channel 2 in Figure 1) are made clear by considering the short-term (i.e. one-period) cash flow constraint of a bank experiencing funding problems. Assume that without undertaking any action, the bank fears that its flow constraint may not be not satisfied in current or future periods. Then, short of defaulting, the bank has several options which could intensify funding pressures at other banks. For example, if the stressed bank draws on its committed credit lines with other banks or chooses to hoard liquidity itself (either by shortening the maturity of loans it is prepared to offer in the interbank market or withdrawing funding altogether), the flow constraints of counterparties will be tightened or put at greater future risk. In many cases, counterparties will be able to obtain funding from alternative sources and this will not matter. But funding problems at institutions which are already stressed could be intensified or there could be an adverse interaction with broader systemic liquidity problems. Moreover, small banks may find it difficult to access alternative sources of funding even if they are not stressed: indeed, the potential loss of a major funding source for small regional U.S. banks was one of the reasons for the bail-out of Continental Illinois in 1984. Yet, despite its potential importance, this 'funding contagion' channel has only received limited attention in the literature, though recent theoretical work by Gai and Kapadia (2009) has shown how this type of action, especially if associated with a key player in the network, can cause an interbank market collapse in which all banks stop lending to each other.

By contrast, asset fire sales (channel 3 in Figure 1) have been widely discussed. The potential feedback loop between distress selling and falling asset prices was first highlighted by Fisher (1933). After the failure of LTCM and the resulting liquidity crisis for Lehman Brothers in 1998, this idea was formalised by a wide range of authors (see Shim and von Peter, 2006, for a survey). Mark-to-market losses associated with falling asset prices could raise solvency concerns at highly exposed institutions and clearly have the potential to propagate the initial funding crisis more widely through the system.[4] Moreover, Brunnermeier and Pedersen (2009) show that severe mark-to-market losses may trigger additional margin calls on off-balance sheet transactions. These may come through negative mark-to market revaluations of the actual positions. Additionally, the value of the collateral backing the margin call may fall. Finally, a rating downgrade may trigger clauses in the contract requiring additional margin (in the form of cash or collateral). Their model can also be recast in terms of the flow constraint: higher margin calls are equivalent to higher liquidity demands from off-balance sheet items ($WL_{New,Ro}$) whilst at the same time, lower asset prices, p_i, reduce available liquidity. A crisis may be deepened further by predatory behaviour (Acharya et al (2008)), or by the incentive for buyers to wait for further asset price declines whilst sellers gamble for resurrection (Diamond and Rajan, 2009).

Ultimately, if, a bank has insufficient funding, it will be forced to default on its obligations, and its financial counterparties are likely to suffer a loss in the interbank market (channel 5 in Figure 1). This may weaken the solvency and thus overall funding position of other banks, with counter-party credit risk linkages possibly propagating the shock possibly even more widely through the financial system (Allen and Gale, 2000; Freixas, Parigi and Rochet, 2000; ; Upper, 2007; Gai and Kapadia, 2010). But it is also clear from the flow constraint that a loss of WL_D could lead to a direct short-term funding problem at a bank even if it remains solvent.

Thus far, we have focussed on the negative system-wide effects of funding liquidity crises. But it is important to note that when funds are withdrawn from a stressed bank, they must be placed elsewhere. So, unless the funds end up as increased reserve holdings at the central bank, some banks are likely to *strengthen* as a result of funding crises through an increase in WL_N and, possibly, RL_N. Indeed, Gatev and Strahan (2006) and Gatev *et al*. (2006) identify this effect in the U.S. banking sector, especially for larger institutions.[5] However, the strength of this countervailing effect is likely to be highly dependent on the type of crisis: in a crisis precipitated by an idiosyncratic shock to one institution, we may expect it to be fairly strong; if much of the banking system is in distress, central bank reserves may end up increasing as happened to a certain extent during the recent financial crisis. Moreover, note that such redistributional effects can only occur if funds are actually withdrawn – they do not help if there is a systemic

[4] Cifuentes, Ferruci and Shin (2005) develop a model along these lines, though their focus is on the pure solvency constraint.
[5] It should, however, be noted that Pennacchi (2006) finds that demand deposit inflows cannot be observed prior to the introduction of deposit insurance, indicating that this effect may be driven by regulatory interventions rather than by the underlying structure of banks' balance sheets.

shortening of the maturity of interbank lending across the system. Therefore, to maintain simplicity, we do not take these effects into account.

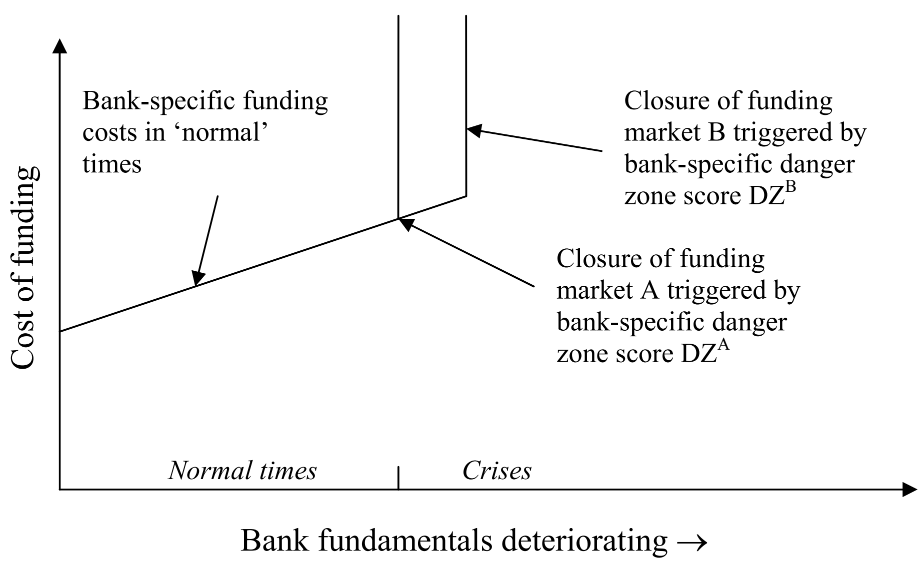
3 Modelling liquidity risk for individual banks – a 'danger zones' approach

Modelling the liquidity risk of an individual bank presents significant challenges. First, we do have not full information on the underlying cash flow constraints. And second, the stochastic nature of each component cannot be properly estimated because of the binary, non-linear nature of liquidity risk, and because liquidity crises in developed countries have been (until recently) rare events for which data are limited. We therefore adopt a simple, transparent (yet subjective) 'danger zone' approach, where we assume that certain funding markets close, if banks solvency and liquidity conditions – summarised by a danger zone score explained below – cross particular thresholds.

Our approach to modelling the closure of funding markets is somewhat stylised. In particular, as discussed in Section 2.1 we take a high level view of the flow constraint and do not consider all different markets for liquidity. But we differentiate between retail, unsecured wholesale, and secured wholesale markets. And we split unsecured funding into longer-term and shorter-term markets. The main findings of the paper are primarily driven by conditions in short- and long-term unsecured wholesale markets. As retail depositors are assumed to be protected by a deposit insurance scheme, they only play a minor role. And, in the current implementation, the closure of secured funding markets does not play an explicit role because it is assumed that banks will always be able to raise the same amount of cash by disposing the collateral at prevailing market prices. In reality, however, a sudden closure of secured funding markets may make it impossible to sell all of the collateral at a sufficiently high price to meet immediate funding needs.

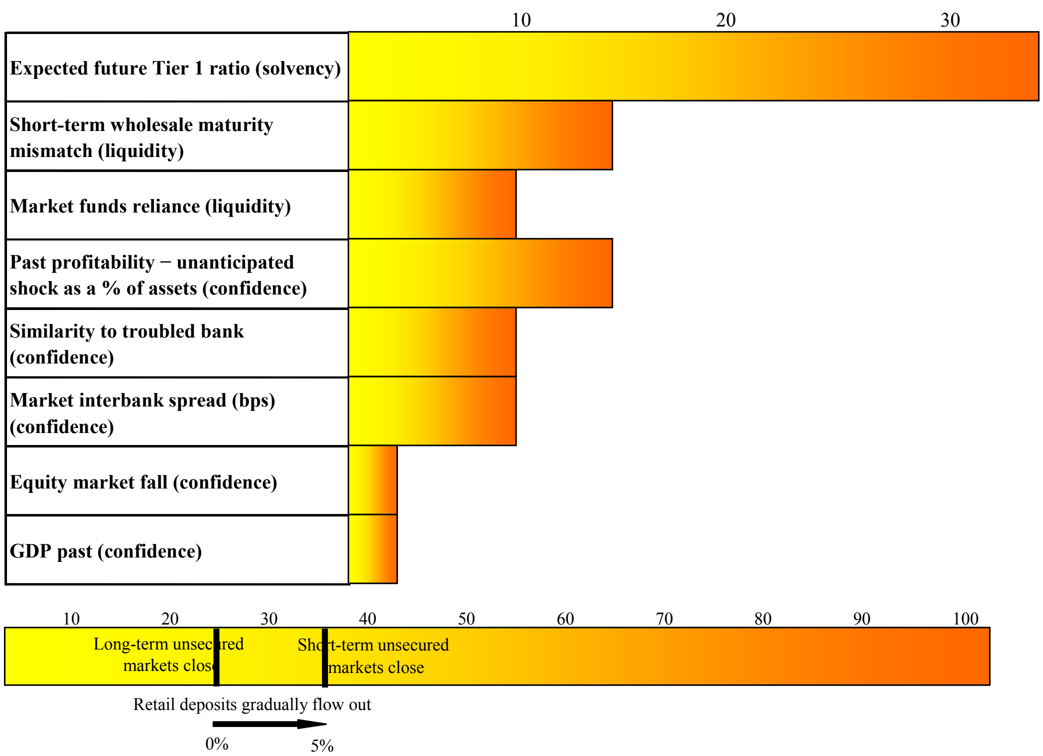
We also only consider normal and crisis times for each funding market. Figure 2 illustrates this point. In normal times, funding is available in all markets. But banks with weaker fundamentals have to pay higher costs. Interbank markets usually do not differentiate widely between different banks (see Furfine, 2002). As a first order approximation, we therefore assume that in 'normal' times the costs in all markets equals LIBOR plus a credit risk premium which increases as ratings deteriorate (for details see Section 5). However, once liquidity risk crystallises, the process is inherently non-linear and may occur at different ratings and funding costs. As there is not reliable data to estimate the price and availability of funds for different fundamentals, we model the non-linearity especially starkly: once fundamentals (as summarized in the danger zone score (DZ)) fall below a certain thresholds, the bank faces infinite costs to access this market, ie the market is closed for this bank. However, crises have shown that different funding markets (A and B) close at different times. As we discussed, it is for example a rational response by lenders to provide short-term funding even though they are not willing to grant long-term loans. Given the focus on unsecured markets, we assume that a danger zone score above DZ^A will lead to a closure of long-term wholesale markets, whilst short-term wholesale markets remain open until the bank breaches the danger zone score DZ^B. A deposit insurance scheme notwithstanding, some unsecured retail deposits (between 0 and 5%) are withdrawn if the danger zone sore is between DZ^A and DZ^B.

Figure 4: A stylised view of funding liquidity risk for an individual bank



The previous discussion highlights that there is not one simple trigger for a funding liquidity crisis at an individual bank. For practical purposes, we supplement the insights from theory with information from individual banks' liquidity policies and contingency plans (and summaries of these including ECB (2002), BIS (2006) and IIF (2007)), and evidence from case studies of funding liquidity crises from this and past crises. As shown in Figure 5, we assume that a set of eight indicators can proxy the three broad areas that theory and experience suggest are important: (i) a weak liquidty position / funding structure; (ii) concerns about future solvency; and (iii) institution-specific and market-wide confidence effects, over and above those generated by solvency concerns or wekanesses in liquidty positions. Weak liquidity positions and funding structures are captured through two metrics. First, a short-term wholesale maturity mismatch compares short-term wholesale liabilities with short-term wholesale assets (including maturing wholesale loans and liquid assets, e.g. government bonds). Second, any longer-term funding vulnerability is captured through a metric that measures reliance on market funds. These metrics assume funds from wholesale counterparties and markets to be flightier than retail deposits. Solvency concerns are captured through a forward-looking Tier 1 capital ratio, based on regulatory measures. Confidence concerns are captured through a number of metrics: unexpected shocks to the previous quarter's profitability (this is kept distinct from solvency concerns which are longer-term in focus); the possibility of confidence contagion is captured through an assessment of how similar the institution is to (other) troubled banks; and three metrics look at market prices (the cost of interbank funding, the size of recent movements in equity markets, and the size of recent movements in GDP).

Figure 5: Danger zones – basic structure



Note that the danger zone approach allows for some feedback effects. In particular, the closure of certain funding markets to an institution: (i) may worsen that bank's liquidity position through ‘snowballing’ effects, whereby the bank becomes increasingly reliant on short-term funding; and (ii) may adversely affect ‘similar’ banks through a pure confidence channel.

Figure 5 also presents the aggregation scheme and the thresholds at which short-term and long-term unsecured funding markets are assumed to close to the bank. In constructing the weighting, we place roughly equal weight on three main factors (liquidity, solvency and confidence) that can trigger funding crises. In the aggregation, we allow for the possibility that a run could be triggered either by extreme scores in any of the three areas, or by a combination of moderate scores across the different areas. The judgements underpinning more specific aspects of the calibration and weighting schemes were informed by analysis of a range of case studies. As an example, Appendix 1 shows the danger zone approach ahead of the failure of Continental Illinois.

4 Modelling Systemic Liquidity Feedbacks

Funding options become more restricted as a bank’s position deteriorates. In this section, we describe how the potential systemic consequences become increasingly severe in two phases of a bank’s funding crisis. The DZ scores outlined in the previous section provide the triggers for various levels of funding stress. A score of 25 or more DZ points triggers the closure of long-term unsecured funding markets to the bank. We refer to this as ‘Phase 1’ of funding market closure. There is no default during this phase since the bank is able to refinance in short-term unsecured funding markets and banks are assumed to have access to an infinite supply of short-term unsecured funding. Once the DZ score reaches 35, short-term funding markets close to the bank, and the bank enters ‘Phase 2’ of funding market closure. But even a very high DZ score does not in itself trigger the failure of the bank – this only occurs if the bank’s capital falls below the regulatory minimum or if it is unable to meet is cash flow constraint.

The anatomy of these phases is described below. Throughout this section, we use the RAMSI balance sheets to run simulations which isolate various liquidity feedbacks. These balance sheets cover the largest UK banks and are highly disaggregated, with a wide range of different asset and liability classes. Each of the asset and liability classes is further disaggregated into a total of eleven buckets (five maturity buckets and six repricing buckets) and these are interpolated so that maturity information for each asset and liability class is available in a series of 3 month buckets (0-3 months, 3-6 months, 6-9 months etc.). RAMSI also includes a matrix of bilateral interbank assets and liabilities for the major UK banks. This is built using reported large exposure data where available. Since we also have information on total interbank asset and liability positions, we then use maximum entropy techniques to fill in missing gaps in the network, ensuring that none of the estimated entries exceed the reporting threshold for large exposures.[6] In general, the balance sheet data are mainly extracted from published accounts but supplemented from regulatory returns. As some balance sheet entries are unavailable, we use rules of thumb based on other information or extrapolations on the basis of our knowledge of similarities between banks to fill in the data gaps.

4.1 Phase 1: Closure of long-term wholesale funding

The loss of access to long-term wholesale funding markets has a direct impact on the bank in question and an indirect impact on other banks in the network, as the affected bank may take defensive actions. These effects operate through banks' short-term wholesale maturity mismatch DZ score. In this section we provide illustrative simulations using the RAMSI balance sheets to highlight these effects. To simplify the analysis, we hold the size of balance sheets constant as time progresses, and also hold all other DZ scores constant apart from the short-term maturity mismatch score.

The closure of long-term wholesale markets implies that the bank has to refinance a larger volume of liabilities in the wholesale markets each period. This increases the maturity mismatch score (MM_t), which is calculated as follows:

$$MM_t = \frac{LA_t + WA_t^{0-3} - WL_t^{0-3}}{TA_t},$$

The mismatch is constructed using wholesale assets ($WA_t^{0\text{-}3}$) and liabilities ($WL_t^{0\text{-}3}$) which have a remaining contractual maturity of less than 3 months in order to capture the short-term position of the bank.[7] TA_t are total assets and LA_t liquid assets.[8] The danger zone scores for the short-term maturity mismatch indicator are shown in Table 1.

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[6] The techniques adopted are similar to those discussed by Wells (2004), Elsinger *et al* (2006b) and OeNB (2006). If any interbank assets or liabilities are unallocated following this procedure, we assume that they are associated with a residual sector which cannot default.

[7] Wholesale assets are defined as loans and advances to banks and other financial companies, financial investments available for sale (excluding items that are recognised as liquid assets) and reverse repurchase agreements. Wholesale liabilities are defined as deposits from banks and other financial companies, items in the course of collection due to other banks and debt securities in issue. Short-term is defined as less than three months due to the constraints of RAMSI's balance sheet structure. Ideally, we would embellish the model with a more granular maturity split of liabilities but the same key dynamics and feedbacks would apply.

[8] Liquid assets are defined as: cash and balances at central banks; items in the course of collection; treasury and other eligible bills; and government bonds.

Table 1 Points score for short-term wholesale maturity mismatch:

Calculated maturity mismatch	Danger Zone Points
Less than -5%	0
-5% to -8%	0-3
-8% to 11%	3-6
-11% to -14%	6-9
-14% to -17%	9-12
-17% to -20%	12-15

We demonstrate the model's properties by presenting results from a stressed scenario in which the various transmission channels are introduced in turn. Results are presented relative to a baseline in which no effects are switched on. We focus on three banks. The 'distressed' bank is the bank that we calibrate to have a Danger Zone score exceeding 25, implying it is shut out of long-term funding markets. We also show the impact on two other banks (Banks A and B). Both are connected to the distressed bank though the interbank network and we shall demonstrate how the degree of connectivity affects the magnitude of the spillovers.

(i) Snowballing into shorter-term maturities (Chart 1.1): Once the distressed bank loses access to long-term unsecured wholesale funding markets, it substitutes lost long-term unsecured wholesale funding for short-term wholesale unsecured funding. This is the snowballing effect. Chart 1.1 illustrates that snowballing increases the distressed bank's short-term wholesale maturity mismatch (expressed as a percentage of total assets according to the equation above) each quarter as more of its liabilities mature and are rolled over only at short-term maturity. The distressed bank's maturity mismatch as a percentage of total assets worsens by around 4 percentage points over the 12 quarters (shown in Chart 1.1 as a decline in maturity mismatch). The chart illustrates how much of the increase in maturity mismatch impact of snowballing occurs in the first four quarters, with the effect tailing off over time, reflecting the concentration of liabilities in the shorter maturity buckets. By design there is no impact on the other banks.[9]

[9] At this stage we have made the simplifying assumption that there is no corresponding shortening of the maturity of assets of other banks, since this is likely to be of only second order importance in its impact on funding conditions.

Chart 1: The evolution of maturity mismatch under different assumptions

Chart 1.1 Impact of Snowballing only

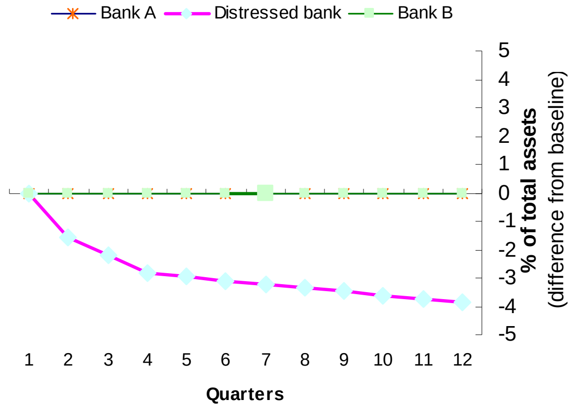


Chart 1.2: Impact of Liquidity Hoarding only

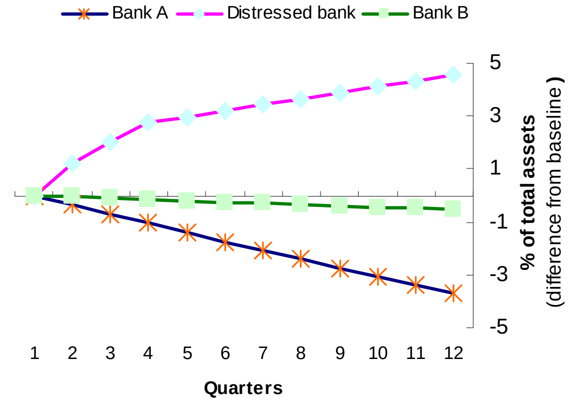
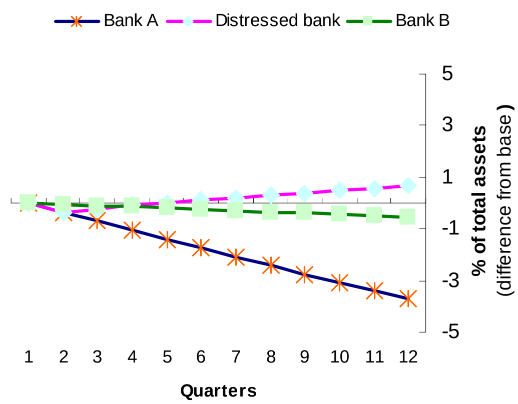


Chart 1.3: Impact of snowballing and liquidity hoarding



(ii) Liquidity Hoarding by Shortening Lending Maturities (Chart 1.2): A bank that is nervous of its future liquidity position takes the defensive action of hoarding liquidity by maturity, only rolling over maturing wholesale assets at short-term maturities (ie less than three months in our setup). This has two effects. First, the additional short-term wholesale assets improve the distressed bank's short-term wholesale maturity mismatch position in the next period as extra liquidity will be available on demand if needed (note that there is no snowballing effect in this example). This serves to improve its maturity mismatch in the next quarter. Chart 1.2 illustrates how the maturity mismatch of the distressed bank improves by nearly five percentage points over the simulation. Second, this behaviour leads to a shortening of the interbank liabilities of other banks to which the distressed bank is lending – as the distressed bank hoards liquidity, some other banks effectively suffer a snowballing effect on a portion of their interbank liabilities. This worsens the other banks' short-term wholesale maturity mismatch position and

thus serves to increase their danger zone points scores – hence this type of liquidity hoarding has adverse spillovers for other banks in the system. Note that bank A's position deteriorates by more than bank B. This is because more of bank A's interbank liabilities are sourced from the distressed bank (this is calibrated using data from the matrix of interbank exposures).

(iii) Snowballing and Liquidity hoarding (Chart 1.3): Allowing for both snowballing and liquidity hoarding is represented as a combination of (i) and (ii) above. In this case, after worsening initially, the distressed bank's maturity mismatch position eventually improves as the impact of liquidity hoarding becomes stronger than the impact of snowballing. Note that this is due to the specific balance sheet structure of this bank – in other cases, snowballing may prove to be the stronger effect. At the same time, other banks' maturity mismatch worsens, since there is only the negative impact of the distressed bank's liquidity hoarding, the effect of which is identical to case (ii) since the amount of liquidity hoarded by the distressed bank is the same in each case.

(iv) Outflow of retail deposits: After long-term unsecured funding markets close to the bank, the bank experiences gradual retail deposit outflows (0.5% for every danger zone point above 25) such that the outflow reaches 5% of retail deposits by the time short-term unsecured markets close. This is intended to reflect behaviour of well-informed investors rather than representing a widespread (Northern Rock style) run. The bank replaces lost retail deposits with short-term wholesale unsecured funding. Similar to the impact of snowballing, this worsens its short-term wholesale maturity mismatch position and thus serves to increase its danger zone points score in the next quarter.

In most circumstances a stressed bank will survive this phase of a funding crisis, since it can still access short-term funding markets. But if its mismatch position worsens, its danger zone score will be increasing. Therefore, the bank may be accumulating vulnerabilities which place it at greater risk of losing access to short-term funding markets in future periods.

4.2 Phase 2: Closure of short-term wholesale markets

The second phase of the liquidity crisis occurs when funding conditions deteriorate to such an extent that the bank is frozen out of both short- and long-term funding markets. In our model, this occurs when a bank's DZ score exceeds 35 (see Figure 5). The bank's insolvency is not inevitable at this point. But having lost both short- and long-term wholesale funding, it becomes increasingly difficult for the bank to meet its cash flow constraint. Therefore, it may need to take further defensive actions.

The possible systemic consequences of funding crises are made clear by considering the short-term (i.e. one-period) cash flow constraint of a bank experiencing funding problems. In particular, suppose that a bank faces a liquidity crisis and cannot or anticipates not being able to access new funding from wholesale markets ($WL_{New,Ro} = 0$ in equation (1)). Then, short of defaulting, the bank has four options affecting the left or right hand side of the cash flow constraint. It can:

1) use profits (net income) to pay off maturing liabilities;
2) choose not to roll over or grant new funding to other financial institutions ($WA_{New,Ro}$) (liquidity hoarding by withdrawal of funding);
3) choose not to roll over or grant new loans to non-financials ($RA_{New,Ro}$);
4) sell illiquid assets ($\Sigma p_i * ILA_i^S$).

Note that in practice banks have further options, which we exclude in our simulations. First, they could draw down committed credit lines with other banks. In principle, this may be a preferred option, but experience in the financial crisis has demonstrated that a stressed bank cannot always rely on being able to draw on such lines. And any such drawdown may, in any case, send an adverse signal to the markets, further undermining confidence. Second, banks could contract lending to the real economy. This will improve the flow constraint but at the same time may have severe repercussions for the macroeconomy.[10] The incorporation of macroeconomic feedbacks is not addressed within this paper but is the subject of ongoing development work. Given this, we assume that banks continue to replace maturing retail assets with new retail assets ($RA_{New} = RA_{Due}$). Finally, we assume that all retail liabilities can be refinanced beyond the 5% outflow already captured between 25 and 35 points ($RL_{New} = RL_{Due}$). This assumption could be easily relaxed, but seems realistic given current deposit insurance frameworks.

It is unclear how banks would weigh up the relative costs of these choices in practice. But the ordering above reflects our judgement on the sequencing of banks' defensive actions. This is based both on an intuitive judgement of the costs imposed to the bank in distress by each action,

[10] For the impact of liquidity shocks on real lending during the recent crisis see e.g. Ivashina and Scharfstein (2009). Huang (2009) provides evidence that distressed banks reduced the available of pre-committed credit lines to non-wholesale customers.

information from banks' own contingency planning documents, and an assessment of the defensive actions actually taken by banks during the recent financial crisis

4.2.1 The implications of the various funding options

Once short-term wholesale funding options are removed, a preliminary check is made during the simulation to determine if the bank is able to meet its cash flow constraint in the complete absence of wholesale funding. If so, and subject to the above assumptions, the constraint is satisfied and they can proceed to the next quarter. If not, then we consider how banks may take the defensive actions outlined above to help them meet the constraint (options 1-4). Any bank that does not satisfy the constraint after all options are chosen is defined as defaulted.

Option 1: Using profits to repay liabilities. Using profits to repay maturing liabilities is likely to have a limited marginal impact on funding markets' confidence in the bank, and so is ordered as the first defensive action taken by a bank excluded altogether from wholesale funding markets. But banks are only likely to be able to raise limited funds in this way, especially in circumstances where low profitability has contributed to funding difficulties.

Option 2: Liquidity Hoarding (WA_{New} equal to zero). In practice, liquidity hoarding has probably been the most frequently observed defensive action during the recent financial crisis. Liquidity hoarding allows funds to be raised quickly and may be perceived as only having a limited impact on the franchise value of the bank. Furthermore, although such hoarding may involve some reputational costs, these may seen as less severe than those resulting from other options.

Given the ordering of actions we assume, a bank which has lost access to short-term funding will already be hoarding liquidity by shortening the maturity of its wholesale lending. But now we assume that it stops rolling over or issuing new wholesale loans completely. The proceeds from the maturing assets are used to repay maturing wholesale liabilities. The balance sheet shrinks as a result. But there is no direct impact on counterparties – we assume that those that are below 35 points can replace the lost funding with new short-term interbank liabilities in the interbank market, while those that are above 35 points will already have lost access to short-term wholesale funding markets in any case.

Option 3: Adding unencumbered liquid assets to the inflows. If the cash flow constraint still cannot be met, we assume that banks encumber a fraction of their liquid assets to obtain repo funding to repay liabilities due. Sales or repo of highly liquid assets are possible even in the most severe of crises, but such sales are unlikely to be a first line of defence. Their use depletes reserves, making banks more susceptible to failure in subsequent periods. That said, selling or repoing liquid assets is likely to be preferable to selling illiquid assets, due to the real costs imposed by the latter course of action.

The size of the balance sheet does not change in this step but banks' liquid assets are recorded as encumbered rather than unencumbered and remain as encumbered for the next quarter, meaning that they can no longer be counted as liquid assets in the danger zone measures and can no longer be used in a defensive way if the bank experiences further outflows in the next quarter.

Option 4: Asset Fire Sales. Finally, banks may raise liquidity by selling assets in a fire sale. Fire sales are likely to be associated with a real financial loss and a corresponding hit to capital. They may also be more easily observable in the market, potentially creating severe stigma problems. Given this, we assume that they represent the last course of action. In the implementation, such fire sales are restricted to the pool of available-for-sale (AFS) assets that a bank has. If the bank does not have enough assets to sell to meet its flow constraint, then it fails.

Fire sales also create asset-side feedbacks that cause remaining banks to suffer temporary (intra-period) mark-to-market losses. The fire sale discount lasts for one quarter, and the resulting fall in asset prices may lead other banks to incur mark-to-market losses; hence in extreme circumstances these banks may then also suffer funding liquidity crises. The associated price impact given by equation (2) is applied to other banks' AFS assets. Consistent with Duffie *et al* (2007), we take the relationship between prices and the magnitude of fire sales to be concave. For asset j, the fire sale equation is:

$$P_j' = \max\left\{0, P_j\left(2 - \exp\left(\theta \frac{S_{ij}}{M_j + \varepsilon_j}\right)\right)\right\} \tag{2}$$

The price of asset j following the fire sale, P_j', is the maximum of zero and the price before the fire sale, P_j, multiplied by a discount term. The discount term is a function of value of assets sold by bank i in the fire sale, S_{ij}, divided by the depth of the market in normal times, M_j, and scaled by a parameter θ that reflects frictions, such as search problems, that cause markets to be less than perfectly liquid. Market depth can also be shocked by a term ε_j to capture fluctuations in the depth of markets as macroeconomic conditions vary. There are three types of assets that can be affected by fire sales: equities, corporate debt securities, and asset and mortgage-backed securities. Each has a different value of market depth.

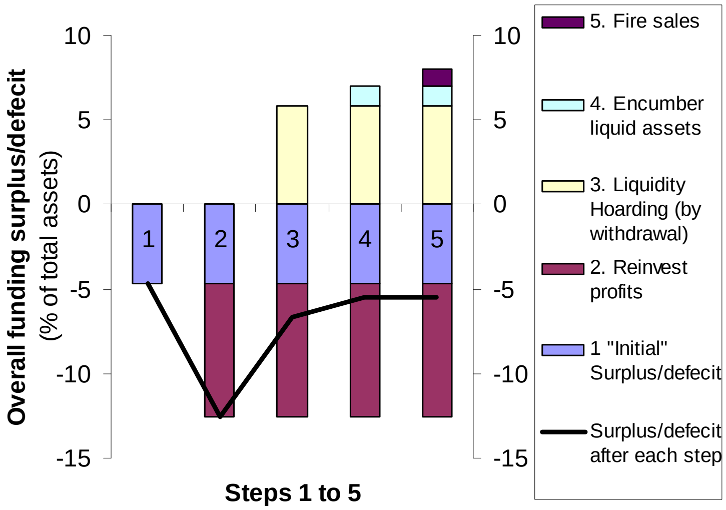
Calibration is guided both by this empirical evidence and a top-down judgement regarding the plausible impact of a fire sale on capital.[11] The calibration for θ is based on the results presented in Mitchell *et al* (2007). Given θ, a value of market depth M_j is chosen for each of the asset types so that when the UK bank with the largest holdings of an asset class in its trading portfolio and AFS assets sells all these assets, it generates prices falls of 2% for equities, 4% for corporate debt, and 5% for asset and mortgage-backed securities.

4.2.2 Crisis funding, a graphical illustration

Chart 3 illustrates the above mechanism with a simulation representing an outcome for one bank. Following a particular shock to fundamentals, the bank does not initially meet the flow constraint once it has been excluded from short- and long-term funding markets. In the example, the bank has a shortfall of around five percent of total assets (the first bar in the chart). Hence the bank moves to Option 1. In the simulation example, the bank is not able to ameliorate its funding position from profits since it makes losses, which actually imply that it is further away from being able to meet its funding constraint. The solid line in Chart 3 illustrates that the bank gets closer to meeting its flow constraint by withdrawing all maturing wholesale assets and using them to pay off liabilities due (Option 2); by encumbering its liquid assets (Option 3) and by increasing its liquid asset holdings through fire-selling its illiquid assets (Option 4). But in this extreme example, the combined effect of these actions is insufficient for the bank to meet its flow constraint and the bank fails.

[11] The impact is likely to be stronger when the financial system is under stress and markets are less deep (Pulvino (1998)).

Chart 2: Steps in flow constraint when wholesale funding withdrawn



4.3 Phase 3: Systemic Impact of a bank's failure

If, after exhausting all potential options, a bank cannot meet its flow constraint, it is assumed to default. When a bank defaults, counterparty credit losses incurred by other banks are determined using a network model. This model operates on RAMSI's interbank matrix and is cleared using the Eisenberg and Noe (2001) algorithm. This returns counterparty credit losses for each institution.

Both fire sale and network feedback effects affect other banks' danger zone points scores. If any of the banks reach 25 points as a result, then they are flagged as snowballing and liquidity hoarding by shortening, and this affects balance sheets in the next quarter as outlined under Phase 1. If the score of any bank crosses 35 points, then that bank enters Phase 2, in which case their defensive actions or failure may affect other banks. This process is continued in a loop until the system clears.

4.4 Summary of systemic feedback effects

To summarise, we can see how the framework captures all of the feedback effects depicted in Figure 1. Confidence contagion is modelled directly within the danger zone scoring system while liquidity hoarding by shortening maturities is an endogenous response to a weak danger zone score which can, in turn, worsen other banks' danger zone scores. Pre-default fire sales can occur as a bank tries to meet its cash flow constraint when it is completely shut out of funding markets, and counterparty credit risk crystallises upon default.

5 Shocks to fundamentals and liquidity risk

So far we have analyzed liquidity risk and associated systemic feedbacks in an isolated fashion. In the remainder of the paper, we integrate these mechanisms into a model simulating banks' profitability from fundamentals. This allows us to determine the impact of introducing liquidty risk and systemic feedbacks for overall system risk, measured here by the system wide asset and loss distribution. Before we show the simulation results, we present a high level overview of RAMSI, the model we use to simulate fundamental shocks (for a detailed discussion see Aikman et al (2009)).

Figure 6: RAMSI framework

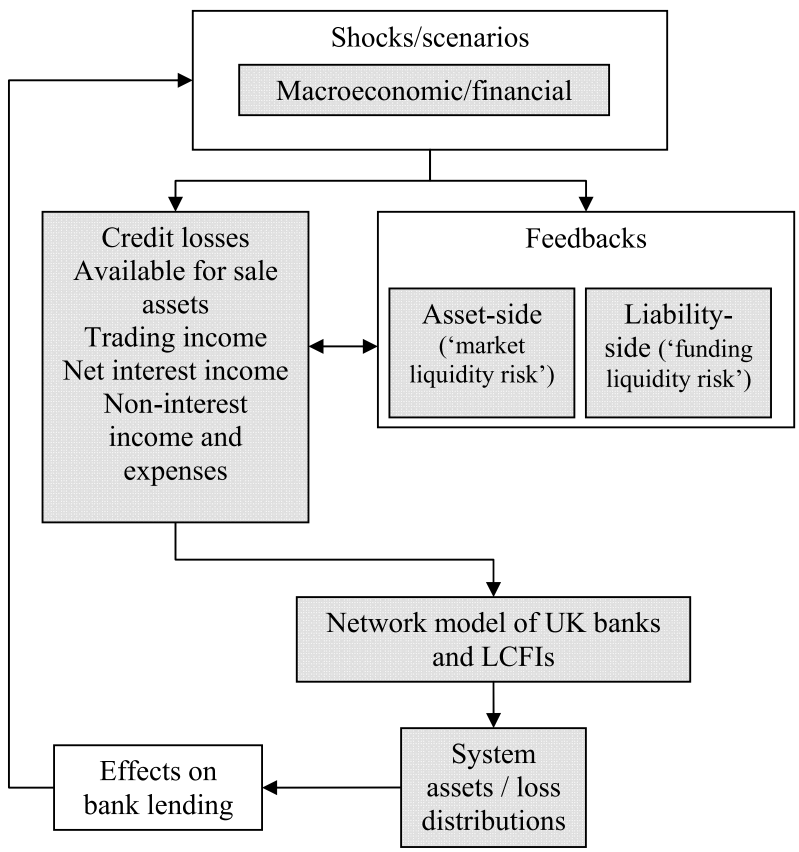
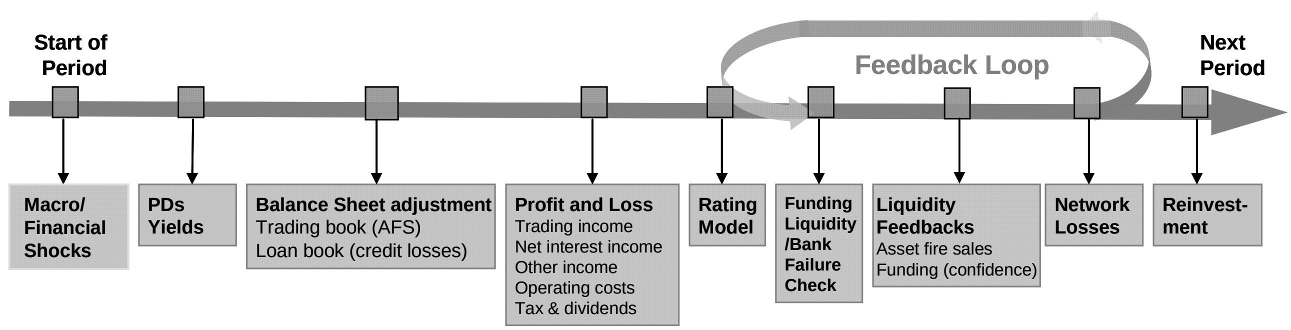


Figure 6 illustrates the modular structure of RAMSI and the mapping from shocks to systemic risk. The transmission dynamics hinge crucially on two factors – the nature and scale of shocks and the structural characteristics of the financial system. RAMSI produces asset distributions for individual banks and for the aggregate banking system by linking together the shaded modules presented in Figure 6. The unshaded module – feedbacks to the macroeconomy – is left for future work.

RAMSI's modular structure is based on comprehensive individual bank balance sheets (as described above), supporting an analytically rich model that allows us to examine the likely sources of profits and losses on a disaggregated and aggregated basis. This version of RAMSI contains balance sheets of the group of the ten largest UK banks as at end-2007.[12]

Figure 7: Model dynamics*



* The trading book and available for sale (AFS) assets are not included in this version of RAMSI.

The sequence of events, including liquidity feedbacks, is illustrated in Figure 7. The model can be run over any time horizon, though the simulations presented below use a three-year horizon, sufficient time for some adverse shocks to be reflected in credit losses, and consistent with the horizon central banks often use when stress testing their financial systems (Hagen et al (2005), Bank of England (2007) and Sveriges Riksbank (2007)).

The first round effects (up to the start of the feedback loop in figure 7) are discussed more fully in Aikman *et al* (2009). We use a large-scale Bayesian VAR (BVAR) to capture the evolution of macroeconomic and financial variables. The BVAR is the only source of shocks in RAMSI, thereby preserving a one-for-one mapping from macroeconomic variables to default risk (as well as liquidity risk), which is useful for story telling purposes. The BVAR is estimated on quarterly data over the sample period 1972 Q2-2007 Q4. The model includes 24 domestic and

[12] Membership of the major UK banks group is based on the provision of customer services in the United Kingdom, regardless of country of ownership. This paper uses end-2007 balance sheets, at which time the members were: Alliance & Leicester, Banco Santander, Barclays, Bradford & Bingley, Halifax Bank of Scotland, HSBC, Lloyds TSB, Nationwide, Northern Rock and Royal Bank of Scotland.

foreign (US and EU) variables and has two lags.[13] Our prior treats every variable in the system as a white noise process centred on a constant. This is a special case of the Minnesota prior popularised by Litterman (1986): essentially, we adapt the standard Minnesota prior to the case where all unit roots have been eliminated by data transformations.[14]

The credit risk module treats aggregate default probabilities (PDs) and loss given default (LGD) as a function of the macroeconomic and financial variables from the BVAR. Credit losses are derived as the product of the relevant aggregate PD times LGD times each bank's total exposure to the sector,[15] though we adjust the aggregate write-off rate for each bank to account for heterogeneity in the riskiness of banks' portfolios.[16] We model credit losses arising from exposures to UK households (mortgages, credit card, and other unsecured borrowing), UK corporates, plus households and corporates in the United States, euro area and rest of the world.

For most of the loan book, interest income is modelled endogenously. Banks price their loans to households and corporates on the basis of the prevailing yield curve and the perceived riskiness of their debtors: an increase in actual or expected credit risk translates into a higher cost of borrowing. We use the risk-neutral asset-pricing model of Drehmann *et al* (2009) to capture both sources of income risk in a consistent fashion. For other parts of the balance sheet, including all of the liability side, we calibrate spreads based on market rates and other data. For example, we assume that interbank assets and liabilities receive/pay the risk-free rate plus the Libor spread, while banks pay negative spreads relative to the risk-free rate on some household and corporate deposits (if the negative spread implies a negative interest rate, the interest rate paid is assumed to be zero).

As long as banks are able to fund themselves in interbank markets, spreads depend on the credit rating of the bank in question. These spreads are modelled endogenously in two stages. First, we use an ordered probit model (adapted from Pagratis and Stringa (2009)) to examine the

[13] The selection criteria for variables include their contribution to explaining macro-developments and also their contribution to explaining developments on balance sheets. The UK variables are real GDP, CPI inflation, Real FTSE All-Share, the yield curve, unemployment, real house prices, real commercial property prices, income gearing, corporate lending, 10 year corporate spread For each of the United States and Euro area we include CPI, real GDP, the 3-month T-Bill rate and the 10-year Government bond rate. We also include real oil prices and world equity prices.

[14] In a Bayesian context, all parameters are treated as random variables and the data are used to estimate their probability distribution rather than to obtain point estimates. We abstract from model uncertainty and use means of the estimated posterior parameter distributions.

[15] That is, we model 'expected credit losses', and trace out variation in expected credit losses driven by macro fundamentals.

[16] These adjustments are made on the basis of historical differences between write-off rates of individual banks and aggregate write-off rates. This implies that a relatively 'safer' bank continues to incur lower credit losses than the typical bank.

sensitivity of Moody's senior (long-term) unsecured ratings to a number of key bank performance indicators and macroeconomic variables. The assigned ratings are mapped to credit spreads using Merrill Lynch's indices of UK sterling bond spreads associated with different credit ratings. This approach implies that if the fundamentals of a bank deteriorate, its credit rating may be downgraded, increasing its future funding costs. We also include simple models for non-trading income and operating expenses but assume that trading income is fixed and exclude portfolio gains and losses on AFS assets, given the difficulties in modelling these components of profit and loss and the fact that they are not the focus of this paper. Profits are then computed as the sum of all sources of income, net of expenses and credit losses. We deduct taxes and dividends from profits, assuming that the tax rate and ratio of dividends to profits are in line with recent history.

At this point, we have all the information we need to assess the danger zone score and we simulate the sequence of events as described in Section 4. In the absence of bank failures, or after the feedback loop has completed, we update the balance sheets of surviving banks using a rule of thumb for reinvestment behaviour. Banks are assumed to target pre-specified Tier 1 capital ratios, and invest in assets and increase liabilities in proportion to their shares on their initial balance sheet, unless the bank faces high liquidity pressures and diverts some or all of reinvestment funds to meet liquidity needs (Step 2 in Phase 2).

6 Simulation Results

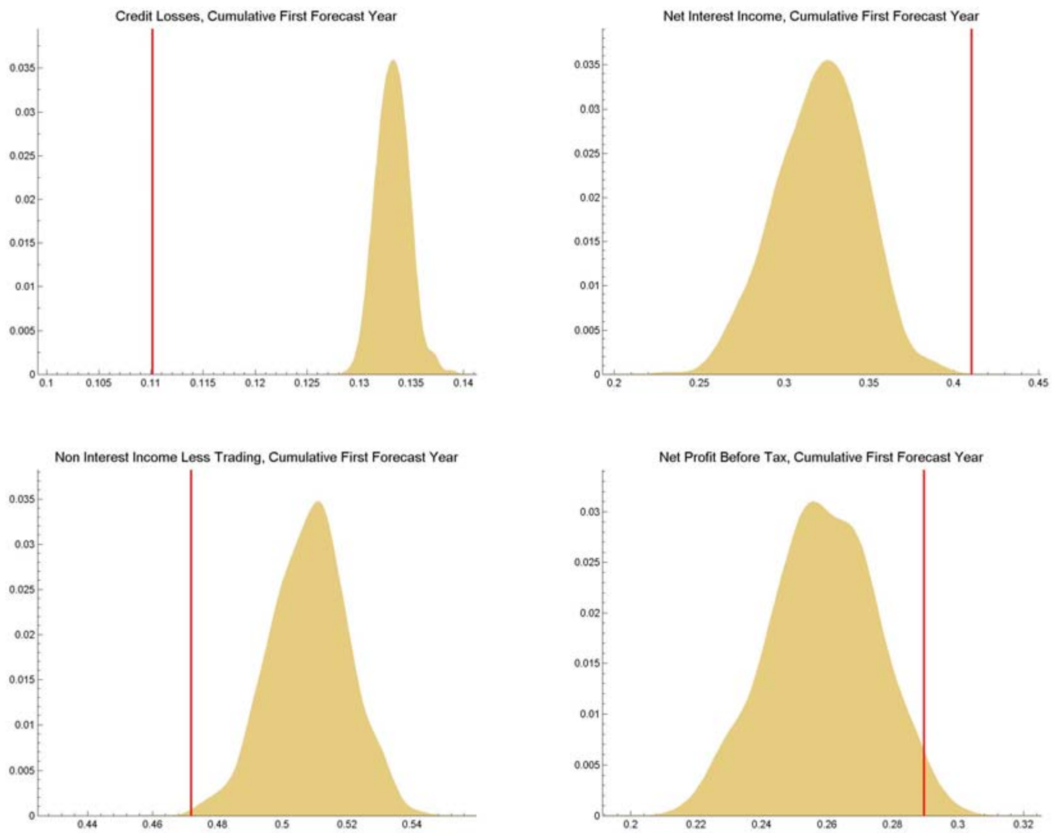
In this section we reveal model properties through stochastic simulations. We use data up to 2007 Q4 (so that all information is on the basis of end-2007 data) and run 500 simulations on a three-year forecast horizon stretching to the end of 2010. The BVAR is the only source of exogenous randomness in the stochastic simulations; each simulation is thus driven by a sequence of macroeconomic shocks drawn from a multivariate normal distribution.[17] The results are illustrative, reflecting model properties in this preliminary version rather than being the authors' view of the likely impact on the banks in question.

Chart 3 shows the simulated distributions of some key profit and loss items, which apply if systemic liquidity feedbacks are not included. For each variable, we calculate aggregate

[17] In other words, we draw 500 realisations of the macroeconomic risk factors in the first quarter. In subsequent periods, we draw a single set of macroeconomic risk factors for each of the 500 draws.

cumulative figures for the first year by adding over banks and quarters, and normalise by aggregate 2007 ('beginning of period') capital. The vertical line represents the corresponding figures from the 2007 published accounts, normalised by 2006 capital levels.

Chart 3: Simulated distributions for profit and loss items: no liquidity effects



Note: in per cent of aggregate 2007 capital. Red vertical line represents the corresponding figures from the 2007 published accounts, normalised by 2006 capital levels.

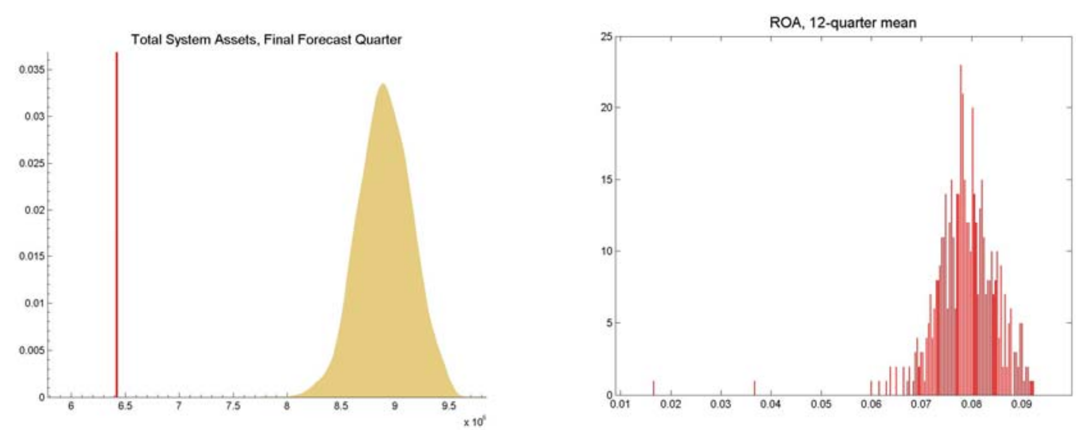
The top left-hand panel shows that credit risk is projected to increase in 2008, reflecting a worsening of the macroeconomic outlook. Net interest income is projected to be weaker than 2007, reflecting higher funding costs and contractual frictions that prevent banks from instantaneously passing on higher funding costs to their borrowers. The variance of net interest income may be unrealistically high as the model does not currently incorporate hedging of interest rate risk.[18] Non-interest income (bottom left-hand panel) remains high, with a median projection above the reported 2007 level; this variable is procyclical but adjusts relatively slowly

[18] Banks can be penalised under the second pillar of Basel II for not hedging interest rate risk in their banking book.

to macroeconomic changes. The net impact on banks' profitability is summarised in the net profit chart (bottom right-hand panel). As can be seen, profits were projected to be weaker than in 2007.

Chart 4 shows the distribution of total assets in the last quarter of the simulation and the average aggregate return on assets (RoA) over the whole 3 year horizon with funding liquidity risk and systemic liquidity feedbacks excluded from the model. This implies that institutions can only default if they become insolvent because their capital falls below the regulatory minimum. It also implies that there is no contagion. As can be seen, the ROA chart has negative skew and some observations in the extreme tail. The negative skew reflects cases where one institution defaults for pure solvency reasons; the extreme observations reflect cases where more than one institution defaults for pure solvency reasons.

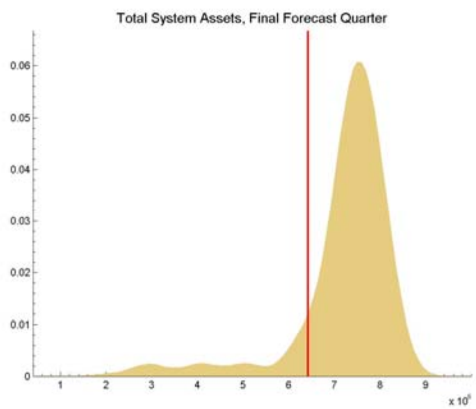
Chart 4: Total system assets – final quarter (no liquidity effects)

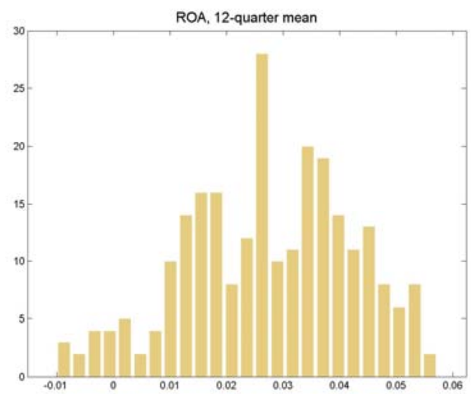


Note: in per cent of aggregate 2007 capital. Red vertical line represents total system assets from the 2007 published accounts, normalised by 2006 capital levels.

Chart 5 presents the results incorporating funding liquidity risk and systemic liquidity feedbacks. It is immediately evident that the final projected outcomes are considerably worse. This is partly due to a higher incidence of failure due to the possibility that an institution may default because it is unable to meet its cash flow constraint. But the charts also highlight the role of contagion due to the systemic feedbacks. The distributions have a long left-hand tail, which is a direct consequence of the feedbacks, which can in some cases cause several institutions to default. These illustrative results point towards the importance of considering funding liquidity risk and systemic feedbacks in any quantitative model of systemic risk.

Chart 5: Total system assets – final quarter (with liquidity effects)





Note: in per cent of aggregate 2007 capital. Red vertical line represents total system assets from the 2007 published accounts, normalised by 2006 capital levels.

By adding on various components one-by-one, it is also possible to use the model to identify how different mechanisms contribute to the profile of systemic risk. For example, the introduction of the simplest danger zone framework (without confidence contagion or snowballing) permits failure even if a bank's capital does not fall below the regulatory minimum and thus worsens the loss distribution. Adding snowballing acts as an amplifier in this regard but may be offset by liquidity hoarding by shortening maturities. Confidence contagion, counterparty defaults and asset fire sales all amplify distress in the tail but allowing for fire sales increase the survival chances of individual banks. It is possible to dissect the tail to identify the particular contributions of these different feedbacks – for an exercise in this spirit which tries to disentangle the effects of (post-failure) fire sales and counterparty default, see Alessandri *et al* (2009).

7 Conclusions and future work

This main contribution of this paper has been to demonstrate how systemic risk may escalate as a bank's funding conditions deteriorate, irrespective of whether the bank ultimately survives or fails. By applying the model to the UK banking system based on the balance sheet vulnerabilities that existed at the end of 2007, we have demonstrated how liquidity concerns can amplify other sources of risk.

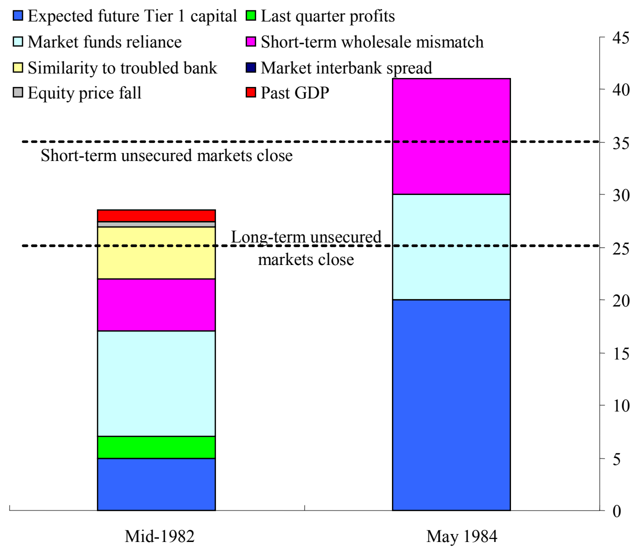
Our quantitative model captures several channels of systemic funding liquidity crises. By imposing a cash flow constraint on each bank, we assess the onset and evolution of liquidity stress in various phases. As distressed banks lose access to longer-term funding markets, their liabilities snowball into shorter-maturities, further increasing funding liquidity risk. Stressed banks take defensive actions in an attempt to stave off a liquidity crisis, which may in turn have a systemic impact. In particular, liquidity hoarding shortens the wholesale liability structure of other banks; while selling assets at fire sales prices may affect the mark-to-market valuation of banks' assets, which in turn affects funding conditions. Beyond this, spillovers between banks may occur due to confidence contagion or via default cascades in the interbank network.

The model could be extended in several ways. For example, rather than generating all shocks from a macroeconomic model, it would be interesting to allow for direct shocks to banks' cash flow constraints, perhaps linked to some underlying aggregate liquidity shock. This would probably reflect the dynamics of the recent crisis more closely. It would also be ideal to capture the evolution of systemic liquidity crises on a more granular basis. With sufficient data, more detailed analysis of liquidity feedbacks over a time period of less than three months should be possible in this framework. But further extensions are likely to be more challenging as they would require a more detailed modelling of optimal endogenous responses to shocks, an area where the theoretical literature has not made much progress yet. Even with the high level cash flow constrained analysed here, this is a highly complex problem as banks would need to optimise over different asset classes and maturity structures taking account of shocks to fundamentals and behavioural reactions of all other market participants. Finally, it would be interesting to use the framework to explore the role that macroprudential policy might be able to play in containing systemic risk.

Appendix 1: An example of a danger zone calibration using Continental Illinois

Case studies indicate that the danger zones approach performs relatively well, especially in terms of capturing the ranking of institutions under most stress. We have considered case studies beyond the very recent crisis. An example is the case of Continental Illinois, which, at least in terms of funding liquidity pressure, can be divided into two periods: the closure of longer-term domestic funding markets to it in July 1982 and the global run in May 1984. Chart A1 scores Continental Illinois in each of these periods.

Chart A1: Continental Illinois danger zone points



Continental scores heavily reliant on the market-funds reliance indicator. But solvency concerns also played a crucial role for Continental. In particular, the July 1982 run may be identified with mild concerns over future solvency stemming from anticipated losses on risky speculative loans to the energy sector. Many of these loans had been originated by Penn Square, a much smaller bank which failed earlier that month. Aside from rising solvency concerns, Continental scores points following Penn Square's failure both because of its similarity and because of a significant unanticipated loss due to a direct exposure. Overall, Continental scores enough points for the first danger zone threshold to be crossed.

After 1982, Continental had greatly reduced access to long-term funding markets. Therefore, increased reliance on short-term funding then served to increase Continental's score over the next couple of years (the snowballing effect). But the final trigger for the second run is the fallout from the Latin American debt crisis – this substantially raised future solvency concerns during the first part of 1984 so that by May, Continental exceeds the second danger zone threshold and ultimately fails.

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