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Liquidity Risk, Cash Flow Constraints, and Systemic Feedbacks

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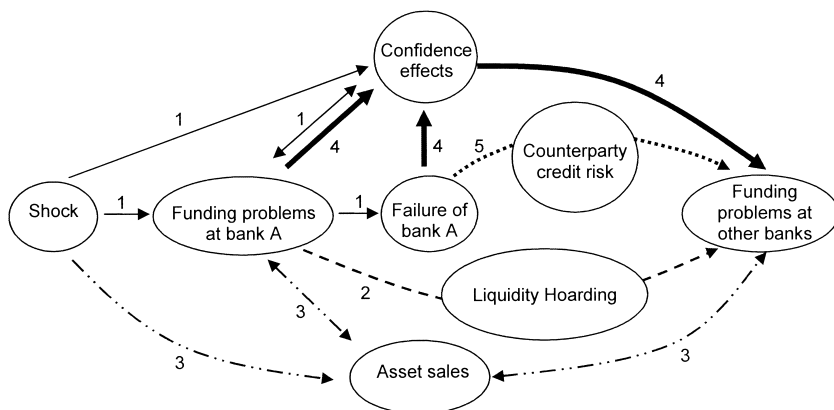
1.1 Introduction

The global financial crisis has served to reiterate the central role of liquidity risk in banking. Such a role has been understood at least since Bagehot (1873). This chapter develops a framework that promotes an understanding of the triggers and system dynamics of liquidity risk during periods of financial instability and illustrates 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 often manifests itself through a crystallization of funding liquidity risk. In a world with perfect information and capital markets, banks would only fail if their

Fig. 1.1   Funding crises in a system-wide context

underlying fundamentals rendered them insolvent. In such a world, provided valuations are appropriate (e.g., adjusted to reflect prospective losses), then examining the stock asset and liability positions would determine banks' 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 and imperfections in capital markets mean that banks may find it difficult to obtain funding if there are concerns about their solvency, regardless of whether or not those concerns are substantiated. In such funding crises, the stock solvency constraint no longer fully determines survival; what matters is whether banks have sufficient cash inflows, including income from asset sales and new borrowing, to cover all cash outflows. In other words, the cash flow constraint becomes critical.

The lens of the cash flow constraint also makes it possible to assess how banks' defensive actions during a funding liquidity crisis may affect the rest of the financial system. Figure 1.1 provides a stylized overview of the transmission mechanisms. For simplicity, it is assumed that the crisis starts with a negative shock leading to funding problems at one bank (bank A). The nature of the shock can be manifold—for example, it could be a negative earnings shock leading to a deterioration of the bank's solvency position or a reputational shock. After funding problems emerge, confidence in bank A may deteriorate further, either endogenously or linked to concerns about the shock (channel 1 in figure 1.1).

In an attempt to stave off a liquidity crisis, the distressed bank may take defensive actions, with possible systemic effects (channels 2 and 3). For instance, it may hoard liquidity. Initially, it may be likely to start hoarding (future) liquidity by shortening the maturities of the interbank market loans it provides. This is advantageous to bank A as shorter-term loans can be realized more quickly and hence may be used as a buffer to poten-

tial liquidity shocks. More extremely, the distressed bank could also cut the provision of interbank loans completely, raising liquidity directly. Both these actions could create or intensify funding problems at other banks that were relying on the distressed bank for funding (channel 2). The distressed bank could also sell assets, which could depress market prices, potentially causing distress at other banks because of mark-to-market losses or margin calls (channel 3). In addition, funding problems could also spread via confidence contagion, whereby market participants decide to run on banks just because they look similar to bank A (channel 4) and, in the event of bank failure, through interbank market contagion via counterparty credit risk (channel 5).

The main innovation of this chapter is to provide a quantitative framework showing how shocks to fundamentals may interact with funding liquidity risk and potentially generate contagion that can spread across the financial system. In principle, one might wish to construct a formal forecasting framework for predicting funding crises and their spread. But it is difficult to estimate the stochastic nature of cash flow constraints because of the binary, nonlinear nature of liquidity risk, and because liquidity crises in developed countries have been (until recently) rare events, so data are limited. Instead, we rely on a pragmatic approach and construct plausible rules of thumb and heuristics. These are based on a range of sources, including behavior observed during crises. This carries the advantage that it provides for a flexible framework that can capture a broad range of features and contagion channels of interest. Such flexibility can help to make the model more relevant for practical risk assessment, as it can provide a benchmark for assessing overall systemic risk given a range of solvency and liquidity shocks.

Our modeling approach disentangles the problem into distinct steps. First, we introduce a "danger zone" approach to model how shocks affect individual banks' funding liquidity risk. This approach is simple and transparent (yet subjective) as we assume that certain funding markets close if the danger zone score crosses particular thresholds. The danger zone score, in turn, summarizes various indicators of banks' solvency and liquidity conditions. These include a bank's similarity to other banks in distress (capturing confidence contagion) and its short-term wholesale maturity mismatch—since the latter indicator worsens if banks lose access to long-term funding markets, the framework also captures "snowballing" effects, whereby banks are exposed to greater liquidity risk as the amount of short-term liabilities that have to be refinanced in each period increases over time. Second, we combine the danger zone approach with simple behavioral reactions to assess how liquidity crises can spread through the system. In particular, we demonstrate how liquidity hoarding and asset fire sales may improve one bank's liquidity position at the expense of others. Last, using the RAMSI (Risk Assessment Model for Systemic Institutions) stress testing model presented in Aikman et al. (2009), we generate illustrative distributions for bank profitability to

show how funding liquidity risk and associated contagion may exacerbate overall systemic risk and amplify distress during financial crises. In particular, we demonstrate how liquidity effects may generate pronounced fat tails even when the underlying shocks to fundamentals are Gaussian.

The feedback mechanisms embedded in the model all played an important role in the current 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 this crisis, interbank lending collapsed from very early on. Spreads between interbank rates for term lending and expected policy rates in the major funding markets rose sharply in August 2007, before spiking in September 2008 following the collapse of Lehman Brothers (figure 1.2, panels A through C, thick black lines). Throughout this period, banks substantially reduced their lending to each other at long-term maturities, with institutions forced to roll over increasingly large portions of their balance sheet at very short maturities. Figure 1.3 highlights these snowballing effects between 2007 and 2008. At the same time, 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, indicative of liquidity hoarding at the system level.

In principle, the collapse in interbank lending could have arisen either because banks had concerns over counterparty credit risk, or over their own future liquidity needs; it is hard to distinguish between these empirically. 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 participants. Interbank spread decompositions into contributions from credit premia and noncredit premia (fig. 1.6, panels A through C), and recent empirical work by Acharya and Merrouche (2012) and Christensen, Lopez, and Rudebusch (2009) all lend support to this view.

It is also clear that the reduction in asset prices after summer 2007 generated mark-to-market losses that intensified 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 (Gorton and Metrick 2010). While 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 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 that had previously been regarded as relatively safe. Counterparty losses also contributed to the systemic impact of its failure, with the fear of a further round of such losses via credit derivative
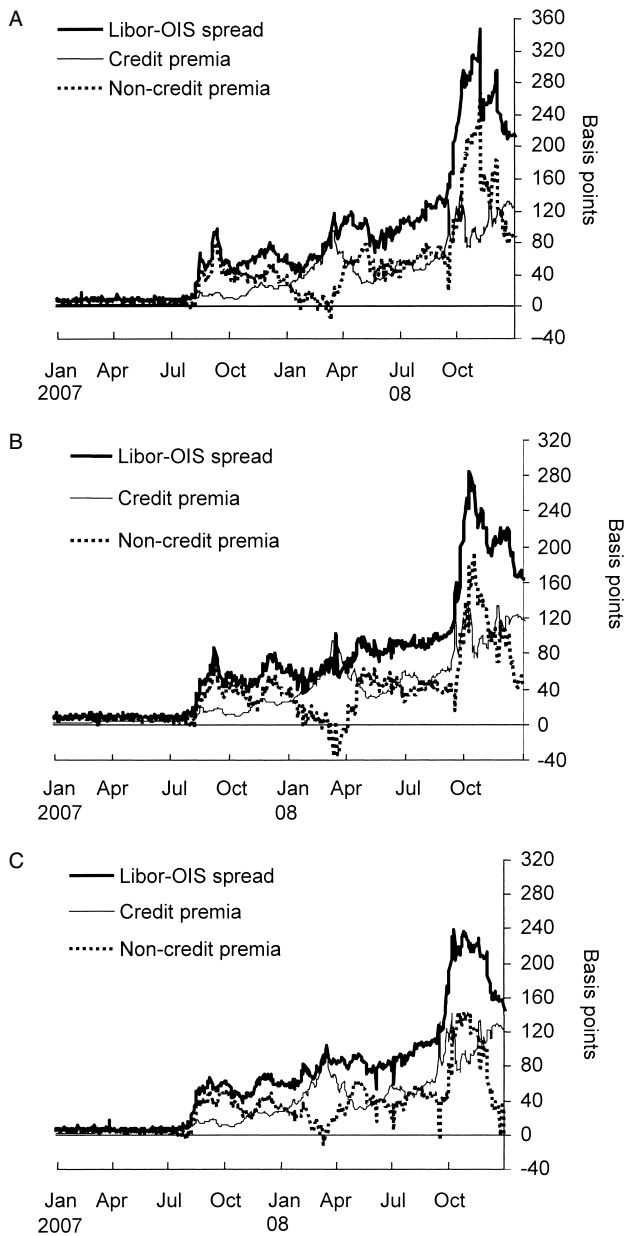
Fig. 1.2   Decomposition of the sterling, dollar, and euro twelve-month interbank spread: *A*, sterling; *B*, dollar; *C*, euro

Sources: British Bankers' Association, Bloomberg, Markit Group Limited, and Bank of England calculations.

Notes: Spread of twelve-month Libor to twelve-month overnight index swap (OIS) rates. Estimates of credit premia are derived from credit default swaps on banks in the Libor panel. Estimates of noncredit premia are derived by the residual. For further details on the methodology, see Bank of England (2007, 498–99).
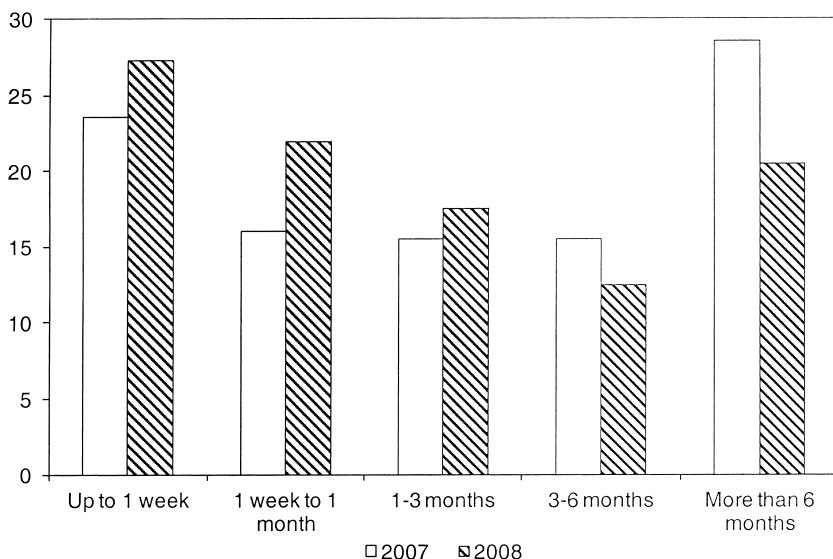
Fig. 1.3   Snowballing in unsecured markets

Source: European Central Bank.

Note: Maturity-weighted breakdown for average daily turnover in unsecured lending as a percentage of total turnover for a panel of 159 banks in Europe. Based on chart 4, section 1.2 of ECB (2008).

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 analyzing how liquidity risk can affect banking systems, some of which we refer to when discussing the cash flow constraint in more detail in section 1.2. 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 analyzes shocks to fundamentals and therefore does not 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). Austrian National Bank (OeNB 2006) and Elsinger, Lehar, and Summer (2006) integrated balance-sheet based models of credit and market risk with a network model to evaluate the probability of bank default in Austria. Alessandri et al. (2009) introduced RAMSI and Aikman et al. (2009) extend the approach in a number of dimensions. RAMSI is a comprehensive balance-sheet model for the largest UK banks, which projects the different items on banks' income statement via modules covering macro-credit risk, net interest income, noninterest income, and operating expenses. Aikman et al.

(2009) also incorporate a simplified version of the danger zone framework developed more fully in this chapter. But in their model, 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 allow for snowballing effects or incorporate banks' cash flow constraints, and do not capture behavioral reactions such as liquidity hoarding or predefault fire sales, all of which are key to understanding the systemic implications of funding liquidity crises.

The chapter is structured as follows. Section 1.2 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 banks' cash flow constraints. Sections 1.3 and 1.4 focus on our quantitative modeling. Section 1.3 provides details on how the danger zone approach captures the closure of funding markets to individual institutions, and section 1.4 presents details and partial simulation results of how behavioral reactions and the danger zone approach interact to create systemic feedbacks. Section 1.5 integrates these effects into RAMSI to illustrate how shocks to fundamentals may be amplified by funding liquidity risk and systemic liquidity feedbacks. Section 1.6 concludes.

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

1.2.1   The Cash Flow Constraint

Liquidity risk arises because inflows and outlays are not synchronized (Holmström and Tirole 1998). This would not matter if agents could issue financial contracts to third parties, pledging their future income as collateral. But given asymmetric information and other frictions, this is not always possible in reality. Hence, the timing of cash in- and outflows is the crucial driver of funding liquidity risk, and a bank is liquid if it is able to settle all obligations with immediacy (see Drehmann and Nikolaou 2012).[1] This is the case if, in every period, cash outflows are smaller than cash inflows and the stock of cash held, along with any cash raised by selling (or repoing) assets:

$$\text{Liabilities}_{(Due)} + \text{Assets}_{(New/Rolled\ over)}$$

$$\leq$$

$$\text{Net Income} + \text{Liabilities}_{(New/Rolled\ over)} + \text{Assets}_{(Due)}$$

$$+ \text{Value of Assets Sold/Repoed}.$$

1. Drehmann and Nikolaou (2012) discuss how this definition of funding liquidity risk relates to other definitions commonly used.

Breaking down these components further:

(1)
$$WL_{Due} + RL_{Due} + WA_{New,Ro} + RA_{New,Ro}$$

$$\leq$$

$$Net\ Income + WL_{New,Ro} + RL_{New,Ro} + WA_{Due} + RA_{Due} + LA^S$$

$$+ \Sigma p_i * ILA_i^S$$

where:

- WL are wholesale liabilities and WA are wholesale assets
- RL are retail liabilities and RA are retail 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 that are contractually due, newly issued or bought, and rolled over, respectively.

We note several issues. First, assessing funding liquidity risk through a cash flow constraint is common in practice (for a recent overview see Matz and Neu 2007) and also forms the basis of elements of proposed new liquidity regulations (Basel Committee 2010). Nonetheless, the literature has tended to model funding liquidity risk differently, even though most theoretical models can be recast in the cash flow constraint as discussed later.

Second, the flow constraint is written in terms of *contractual* maturities as these are the ultimate drivers of funding liquidity risk in crises. But in normal times, the constraint might reasonably be thought of in terms of behavioral maturities that may differ from contractual ones. 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, so RL_{Due} may roughly equal RL_{Ro}. But, in times of stress, depositors may choose to withdraw, so the behavioral maturity may collapse closer to the contractual one.

Third, equation (1) still makes some simplifying assumptions. For example, contingent claims are an important driver of funding liquidity risk. In particular, firms rely heavily on credit lines (see, e.g., Campello et al. 2010). 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 assets or liabilities. Repo transactions are also 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 broadly determines the value that can be raised from

the underlying asset, which may or may not be liquid.[2] Transactions with the central bank are also included under repo. These occur regularly, even in normal conditions, as banks obtain liquidity directly from the central bank during open market operations.[3]

Beyond this, different funding markets split into several submarkets such as interbank borrowing, unsecured bonds, securitizations, commercial paper, and so forth. And there is clearly also a distinction between foreign and domestic funding markets.[4] These separate markets may have quite different characteristics that make them more or less susceptible to illiquidity. Not all factors relevant to funding market dynamics can be easily incorporated into a model of systemic risk. But there are two that we judge to be sufficiently important as well as empirically implementable to split them out separately. First, we differentiate retail funding, secured markets, and unsecured markets. Second, we split unsecured funding into longer-term and shorter-term markets. We discuss these in more detail later in the chapter.

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}, or deposit it at the central bank. Ex ante, however, banks are uncertain as to whether the flow constraint will be satisfied in all periods (i.e., they face funding liquidity risk). The right-hand side of equation (1) shows that this risk is influenced by banks' ability to raise liquidity from different sources for different prices, which will also change over time. The possibilities and implications of their choices are discussed in detail following. Before doing so, it is important to highlight a simple fact that is clear from equation (1): the maturity 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.

1.2.2   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 can always 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

2. In repo transactions, there may also be an additional haircut applied, which would mean that the cash lent on the trade would be lower than the current market value of the security used as collateral. In principle, the flow constraint could be augmented to account for this.

3. Throughout this chapter, we abstract from 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 that would allow banks to obtain more cash from the central bank than they could obtain through asset sales or repo transactions in the market.

4. McGuire and von Peter (2009) identify a shortage of dollar funding as a key driver of non-US banks' funding problems during the current crisis.

funding problems at an individual institution before analyzing how funding crises can spread through the system.

Many 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 (i.e., 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:

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

Under normal circumstances, late depositors roll over their demand deposits ($RL_{\text{Due}}^{\text{late}} = RL_{\text{Ro}}^{\text{late}}$) 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 ($RL_{\text{Ro}}^{\text{late}} = 0$), the bank is forced to start selling its illiquid assets at p_i, which is 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 stylized, this model captures several key features of liquidity crises. First, contractual maturities matter in a liquidity crisis as the "behavioral" 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 equaled its fair value, the bank could always sell assets to satisfy unexpected liquidity demands and would never be illiquid but solvent. Third, confidence and beliefs about the soundness of an institution and the behavior of others play an important role in the crystallization of funding liquidity risk.

The result that confidence effects can, in isolation, drive self-fulfilling bank runs is not particularly realistic: 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; Goldstein 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 banks can still be illiquid but solvent.

1.2.3   System Dynamics of Funding Liquidity Crises

The main focus of our work is to capture the system-wide dynamics of liquidity crises. Figure 1.1 identified several channels through which a funding crisis at one bank could spread to the rest of the financial system. We now relate these dynamics to existing literature and, where appropriate, to the cash flow constraint.

Confidence contagion (channel 4 in fig. 1.1) 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).[5] Alternatively, it could simply reflect panic, whereby investors decide to run on similar banks purely because of sentiment. More generally, system confidence effects can contribute to liquidity hoarding. For example, 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 market player. Anticipating potential funding needs in the future, banks start to hoard liquidity.[6]

The possible systemic consequences of liquidity hoarding (channel 2 in fig. 1.1) are made clear by considering cash flow constraints. For example, if a (stressed) bank hoards liquidity (either by shortening the maturity of loans it offers in the interbank market or withdrawing funding altogether), the flow constraints of counterparties will be tightened or put at greater future risk via a reduction in $WL_{\text{New,Ro}}$. This may intensify funding problems at institutions that are already stressed. And 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 US banks was one of the reasons for the bailout 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, Haldane, and Kapadia (2011) has shown how this type of action, especially if associated with key players in the network, can cause an interbank market collapse in which all banks stop lending to each other.

5. Contagious bank runs can also affect the investment incentives of banks, making system-wide banking crises even more likely (see Drehmann 2002, and Acharya and Yorulmazer 2008).

6. Liquidity hoarding by surplus banks may also be a result of asymmetric information and heightened counterparty credit risk following adverse shocks (Heider, Hoerova, and Holthausen 2009).

By contrast, asset fire sales (channel 3 in fig. 1.1) 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 Long-Term Capital Management (LTCM) and the resulting liquidity crisis for Lehman Brothers in 1998, this idea was formalized by a wide range of authors (see Shim and von Peter, 2007, for a survey). Cifuentes, Ferruci, and Shin (2005) illustrate how mark-to-market losses associated with falling asset prices could raise solvency concerns at highly exposed institutions And Brunnermeier and Pedersen (2009) show how downward spirals between asset fire sales and increased funding liquidity risk can emerge. Such a spiral can, for instance, start if a bank (or broker, as in the Brunnermeier and Pedersen model) is short of funding liquidity, cannot obtain it from the interbank market, and has to sell assets. If asset markets are characterized by frictions, (large) asset sales induce a fall in prices and thus the value of collateral. This, in turn, implies that the bank has to post higher margins, increasing liquidity outflows. To remain liquid banks have to sell even more assets, depressing market prices further.[7] Their model can also be recast in terms of the flow constraint: higher margin calls are equivalent to higher liquidity demands ($WL_{New,Ro}$) while at the same time, lower asset prices, p_i, reduce available liquidity.[8]

Interbank market contagion via counterparty credit risk (channel 5 in fig. 1.1) has also been widely discussed in the literature (Allen and Gale 2000; Freixas, Parigi, and Rochet 2000; Gai and Kapadia 2010; Upper 2011). Clearly, this may weaken the solvency and thus overall funding position of other banks. But it is also evident from the flow constraint that a loss of WA_{Due} 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_{New} and, possibly, RL_{New}. Indeed, Gatev and Strahan (2006) and Gatev, Schuermann, and Strahan (2009) identify this effect in the US banking sector, especially for larger institutions.[9] However, the strength of this countervailing effect

7. Related papers on the amplification role of shocks to margins and haircuts on the securities that serve as collateral in repo transactions include Adrian and Shin (2010), Geanakoplos (2010), and Gorton and Metrick (2010).

8. Shocks to margins or haircuts could also be modeled more directly in the flow constraint by scaling down the value of the $\Sigma p_i * ILA_i^S$ term when interpreted as applying to repo transactions.

9. 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.

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 has happened to a certain extent during this financial crisis. Moreover, such redistributional effects can only occur if funds are actually withdrawn—they do not help if there is a systemic shortening of the maturity of interbank lending across the system. Therefore, to maintain simplicity, we do not take these effects into account in our model.

1.3   Modeling Liquidity Risk for Individual Banks—A "Danger Zone" Approach

Modeling the liquidity risk of an individual bank quantitatively presents significant challenges. One might wish to construct a formal forecasting framework for predicting funding crises. But we do not have full information on the underlying cash flow constraints, and it would be difficult to estimate the stochastic nature of each component because of the binary, nonlinear nature of liquidity risk, and because liquidity crises in developed countries have been (until recently) rare events for which data are limited. Instead, we adopt a simple, transparent (yet subjective) danger zone approach, in which we assume that certain funding markets close if banks' solvency and liquidity conditions—summarized by a danger zone score explained following—cross particular thresholds. In some respects, this is consistent with the broad methodological approach, advocated by Gigerenzer and Brighton (2009), that simple heuristics can sometimes lead to more accurate inferences than approaches that use more information and computation.

Our approach to modeling the closure of funding markets is somewhat stylized. In particular, as discussed in section 1.2.1, we take a high level view of the flow constraint and do not consider all different markets for liquidity. But we differentiate between retail, short-term unsecured wholesale, and long-term unsecured wholesale markets. 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, sudden closures 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 1.4 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 or Angelini, Nobili, and Picillo 2011). As a first-order approximation, we therefore assume that, in "normal" times, funding costs equal a market rate plus a credit risk premium, which increases as ratings deteriorate.
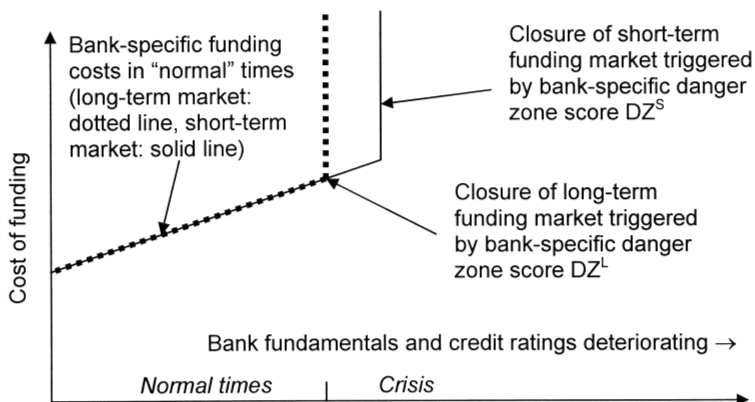
Fig. 1.4   A stylized view of funding liquidity risk for an individual bank

Once liquidity risk crystalizes, the process in different markets is inherently nonlinear and may occur at different ratings and funding costs. We model the nonlinearity especially starkly, but in line with practitioners (see Matz and Neu 2007): once fundamentals (as summarized in the danger zone [DZ] score) fall below certain thresholds, the bank faces infinite costs to access the relevant market (i.e., the market is closed for this bank). Crises have, however, shown that different funding markets close at different times. For example, as discussed earlier, it may be rational for lenders to provide short-term funding even if they are not willing to grant long-term loans. Given this, we assume that a danger zone score above DZ^L 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^S.

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 summaries of individual banks' liquidity policies and contingency plans (European Central Bank [ECB 2002]; Bank for International Settlements [BIS 2006]; Institute of International Finance [IIF 2007]), and evidence from case studies of funding liquidity crises from this and past crises. As shown in figure 1.5, we assume that a set of eight indicators can proxy the three broad areas that theory and experience suggest are important: (1) concerns about future solvency; (2) a weak liquidity position / funding structure; and (3) institution-specific and market-wide confidence effects, over and above those generated by solvency concerns or weakness in liquidity positions.

Solvency concerns are captured through a forward-looking Tier 1 capital ratio, based on regulatory measures. Weak liquidity positions and funding structures are captured through two metrics. First, short-term wholesale maturity mismatch compares short-term wholesale liabilities with short-
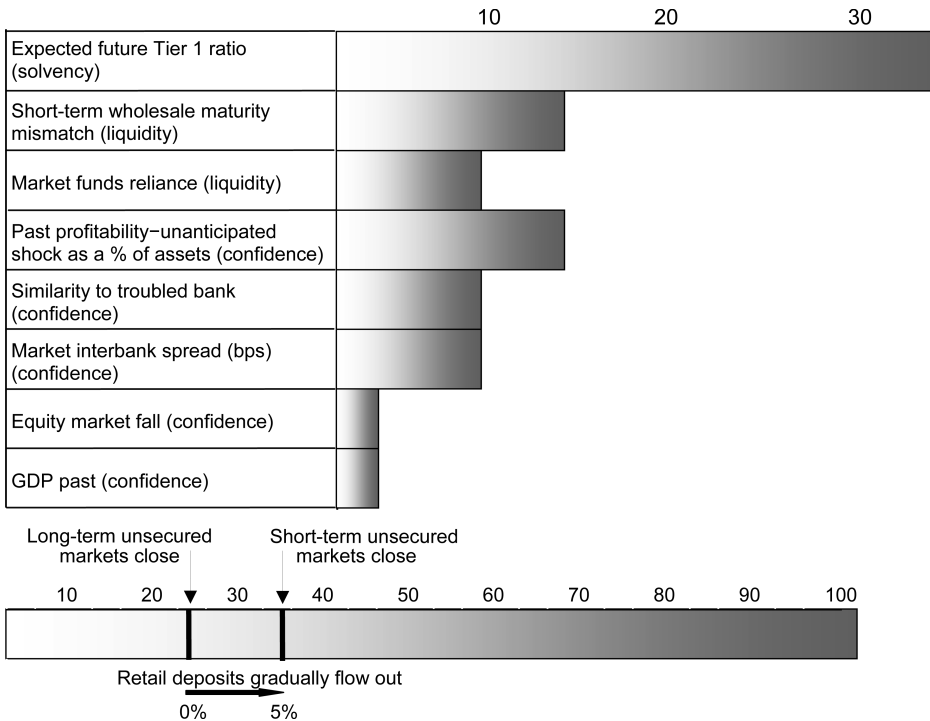
Fig. 1.5 Danger zones—basic structure

term wholesale assets (including maturing wholesale loans and liquid assets). Second, longer-term funding vulnerability is captured through a metric that measures reliance on market funds and shares some similarities to the (inverse of the) core funding ratio applied as a policy tool in New Zealand (Ha and Hodgetts 2011). These metrics assume funds from wholesale counterparties and markets to be flightier than retail deposits. Confidence concerns are captured through a number of metrics: unexpected shocks to the previous quarter's profitability (distinct from solvency concerns, which are longer-term in focus); the possibility of confidence contagion, which is captured through an assessment of how similar the institution is to other troubled banks; and three metrics looking at market prices and real economy data (the cost of interbank funding, the size of recent movements in equity markets, and the size of recent movements in GDP).

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

Figure 1.5 also presents the aggregation scheme and the thresholds at which short-term and long-term unsecured funding markets are assumed to close the bank. Noting that equal weights can predict almost as accurately as, and sometimes better than, multiple regression (Dawes and Corrigan 1974; Dawes 1979), we place roughly equal weight on the three main factors (solvency, liquidity, 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 judgments underpinning more specific aspects of the calibration and weighting schemes were informed by analysis of a range of case studies. As an example, the appendix in this chapter shows the danger zone approach ahead of the failure of Continental Illinois.

Funding options become more restricted as a bank's position deteriorates. At a score of $DZ^L = 25$ points, long-term unsecured funding markets close to the bank. The bank is also assumed to start experiencing gradual retail deposit outflows at this point (0.5 percent for every danger zone point above 25), intended to reflect the behavior of well-informed investors rather than representing a widespread (Northern Rock style) run. 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 $DZ^S = 35$, 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 its cash flow constraint.

1.4   Modeling Systemic Liquidity Feedbacks

As banks' liquidity position deteriorates, they may undertake increasingly extreme defensive actions to try to bolster it. As noted before, such actions may have an adverse effect on other banks. In this section, we provide illustrative simulations using the RAMSI balance sheets to highlight these dynamics quantitatively.

The RAMSI 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 three-month buckets (zero to three months, three to six months, six to nine months, etc.). Given the structure of these data, we define short-term assets and liabilities to be those with less than three months' maturity throughout the simulations. RAMSI also exploits

large exposure data to construct a matrix of bilateral interbank assets and liabilities for the major UK banks.[10]

In general, the balance sheet data are mainly extracted from published accounts but supplemented from regulatory returns. As some balance sheet entries are unavailable, rules of thumb based on other information or extrapolations on the basis of similarities between banks are used to fill in the data gaps. As the simulations in this chapter are purely intended for illustrative purposes, they use balance sheet data for the ten largest UK banks as at end-2007.[11]

1.4.1   Phase 1: Closure of Long-Term Wholesale Markets

The closure of long-term wholesale markets implies that the bank has to refinance a larger volume of liabilities in short-term wholesale markets each period. This increases the short-term wholesale maturity mismatch danger zone score (MM_t):

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

The mismatch is constructed using liquid assets (LA_t), and wholesale assets (WA_t^{0-3}) and liabilities (WL_t^{0-3}), which have a remaining contractual maturity of less than three months, normalized by total assets (TA_t).[12] The danger zone scores for the short-term maturity mismatch indicator are shown in table 1.1.

We demonstrate some of the feedback dynamics embedded in the model by presenting results from a stressed scenario in which 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 from the RAMSI peer group. The "distressed" bank is initially set to have a DZ 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

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10. The techniques adopted are similar to those discussed by Wells (2004); Elsinger, Lehar, and Summer (2006); and OeNB (2006).

11. Membership of the major UK banks group is based on the provision of customer services in the United Kingdom, regardless of country of ownership. At the end of 2007, 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.

12. 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. Wholesale assets are defined as loans and advances to banks and other financial companies, financial investments available for sale (excluding items that are recognized as liquid assets), and reverse repos. Wholesale liabilities are defined as deposits from banks and other financial companies, items in the course of collection due to other banks, debt securities in issue, and repos. 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.

Table 1.1   **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

to the distressed bank though the interbank network and we demonstrate how the degree of connectivity affects the magnitude of the spillovers. 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 wholesale maturity mismatch score.

*Snowballing into Shorter-Term Maturities (fig. 1.6, panel A)*

Once the distressed bank loses access to long-term unsecured wholesale funding markets and starts to experience gradual retail deposit outflows, it substitutes lost funding for short-term wholesale unsecured funding. This is the snowballing effect. Panel A of figure 1.6 illustrates that snowballing worsens the distressed bank's short-term wholesale maturity mismatch each quarter as more of its liabilities mature and are rolled over only at short-term maturity. After three years, it deteriorates by around 4 percentage points. But most of the 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.[13]

*Liquidity Hoarding by Shortening Lending Maturities (fig. 1.6, panel B)*

As argued by Acharya and Skeie (2011), a bank that is nervous about its liquidity position may hoard (future) liquidity by only providing wholesale lending at short-term maturities. This has two effects. First, the additional short-term wholesale assets improve the distressed bank's short-term wholesale maturity mismatch position as extra liquidity will be available on demand if needed. Abstracting from the snowballing effect, panel B of figure 1.6 illustrates how such hoarding can improve the maturity mismatch position of the distressed bank by nearly 5 percentage points over the simulation. Second, this behavior 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

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13. This includes a 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.
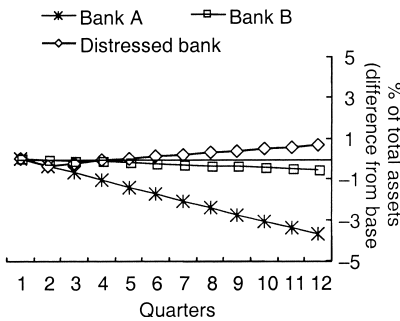
A Impact of Snowballing only
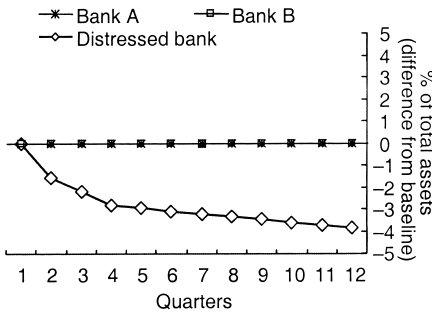
B Impact of Liquidity Hoarding only
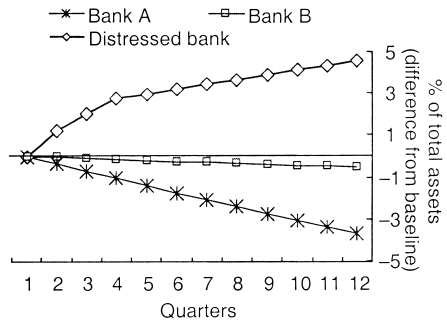
C Impact of snowballing and liquidity hoarding

Fig. 1.6   The evolution of maturity mismatch under different assumptions: *A*, impact of snowballing only; *B*, impact of liquidity hoarding only; *C*, impact of snowballing and liquidity hoarding

effect on a portion of their interbank liabilities. As the bottom two lines in panel B illustrate, this worsens other banks' short-term wholesale maturity mismatch position. It thus serves to increase their DZ points scores—hence, this type of liquidity hoarding has clear 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 (based on data from the matrix of bilateral interbank exposures).

Snowballing and Liquidity Hoarding by Shortening Maturities (fig. 1.6, panel C)

Allowing for both snowballing and liquidity hoarding is represented as a combination of the two previous subsections. 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 they only experience the negative impact of the distressed bank's liquidity hoarding, identical to the case in the previous subsection.

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 increase. Therefore, the bank may be accumulating vulnerabilities that place it at greater risk of losing access to short-term funding markets in future periods.

1.4.2   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 fig. 1.5). Although the bank's insolvency is not inevitable at this point, it becomes increasingly difficult for it 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 ($WL_{\text{New,Ro}} = 0$ 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) earned over the period to pay off maturing liabilities.
2. Choose not to roll over or grant new funding to other financial institutions ($WA_{\text{New,Ro}}$) (liquidity hoarding by withdrawal of funding).
3. Sell or repo liquid assets.
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 this and previous financial crises 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, as set out in many contingency plans (see Matz and Neu 2007), banks could securitize assets. However, this requires some time as well as previous presence in these markets. As the current crisis has demonstrated, it may not be possible in systemic crises. Third, banks could contract lending to the real economy. This will improve the flow constraint but with

potentially severe repercussions for the macroeconomy.[14] However, this is a very slow means of raising liquidity. And as Matz and Neu (2007, 109) put it, a strategic objective of liquidity risk management is to "ensure that profitable business opportunities can be pursued." Given this, we assume that banks continue to replace maturing retail assets with new retail assets ($RA_{New} = RA_{Due}$).

It is unclear how banks would weigh up the relative costs of options 1 through 4. For a start, banks' choice set is not as coarse as can be captured in the model. For example, banks hold a multitude of assets, some of which are less or more illiquid and therefore less or more costly to sell. Actions may also depend on specific circumstances. But we sequence defensive actions in our simulations as ordered earlier. As discussed following, this reflects an intuitive judgement of the costs imposed on the bank in distress by each action, information from summaries of banks' contingency planning documents, and an assessment of the defensive actions actually taken by banks during this financial crisis.

Simulating the Implications of the Various Funding Options

Continuing from phase 1 of funding distress, we now explain how a bank's reaction to losing access to short-term wholesale funding markets may be simulated by using its cash flow constraint. A preliminary check is made to determine if the bank can meet its cash flow constraint in the complete absence of wholesale funding but without accounting for any net income earned over the period, and assuming that banks aim to roll over interbank lending and avoid eroding liquid asset buffers or undertaking fire sales. If so, the constraint is satisfied and the bank survives to the next period. If not, then we consider the following sequence of defensive actions (options 1 through 4). Any bank that does not satisfy the flow constraint after all options are exhausted is defined as defaulted.[15]

Option 1: Using Profits (Net Income) Earned over the Period to Repay Liabilities. In normal times, profits boost bank equity and may be matched on the asset side by higher lending. But banks may also use these proceeds to repay maturing liabilities. This is unlikely to have a significant adverse effect on funding markets' confidence in the bank, and so is ordered first. But banks are only likely to be able to raise limited funds in this way, especially in circumstances in which low profitability has contributed to funding difficulties.

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14. For the impact of liquidity shocks on real lending during the current crisis see, for example, Ivashina and Scharfstein (2010). Huang (2009) provides evidence that distressed banks reduced the availability of precommitted credit lines to nonwholesale customers.

15. Throughout the simulation, we also assume that all retail liabilities can be refinanced beyond the 5 percent outflow already captured between 25 and 35 points (i.e., $RL_{New} = RL_{Due}$).

Option 2: Liquidity Hoarding by Withdrawal of Funding ($WA_{\text{New,Ro}} = 0$). In practice, liquidity hoarding has probably been the most frequently observed defensive action during this financial crisis. From the perspective of individual banks in distress, it allows funds to be raised quickly and may be perceived as only having a limited impact on franchise value. Furthermore, although such hoarding may involve some reputational costs, these may be seen as less severe than those resulting from other options.

In phase 1, a bank that loses access to long-term funding hoards liquidity by shortening the maturity of its wholesale lending. But at this stage, we now suppose 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. For simplicity, this version of the model assumes that there is no direct impact on counterparties—we assume that those that are below 35 DZ points can replace the lost funding with new short-term wholesale 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. It should, however, be noted that in practice, such liquidity hoarding behavior is likely to have adverse systemic consequences by tightening overall funding conditions and causing a deterioration in confidence.

Option 3: Sale or Repo of Liquid Assets. If the cash flow constraint still cannot be met, we assume that banks look to sell liquid assets or use them to obtain repo funding to replace liabilities due. Sales or repo of highly liquid assets are usually possible even in the most severe of crises, but are generally not the first line of defense. Their use depletes buffers, making banks more susceptible to failure in subsequent periods, when other options are exhausted (see Matz 2007). That said, selling or repoing liquid assets is likely preferable to selling illiquid assets, due to the real costs imposed by the latter course of action.

In the simulations, this step is implemented by assuming liquid assets are repoed so that the size of the balance sheet does not change. But banks' liquid assets are recorded as encumbered rather than unencumbered and remain so 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 subsequent periods.

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 easily observable in the market, potentially creating severe stigma problems. Given this, we assume that they represent the last course of action.

In principle, fire sales could apply across a wide range of asset classes,

including in the trading book. But in the simulations, we restrict them to the bank's pool of available-for-sale (AFS) assets due to data limitations. If the bank does not have enough assets to sell to meet its flow constraint, then it fails. The restriction of fire sales to AFS assets makes individual bank failure more likely at this stage than may be the case in practice. But it also limits the extent of contagion to other banks.

The asset-side feedbacks associated with fire sales are modeled by assuming that other banks suffer temporary (intraperiod) mark-to-market losses. This can increase their DZ score via the solvency indicator. In extreme circumstances, these banks may then also suffer funding liquidity crises. The pricing equations used to determine mark-to-market losses on different types of assets follow Aikman et al. (2009)—the key difference with that approach is that fire sales and associated contagion occur *before* rather than upon bank failure.

Crisis Funding, a Graphical Illustration

Figure 1.7 illustrates the aforementioned mechanisms with a simulation representing an outcome for one bank. Its cash flow constraint is estimated using the RAMSI balance sheet data. 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 5 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 from meeting its flow constraint. The solid line in figure 1.7 illustrates that the bank gets closer to meeting its
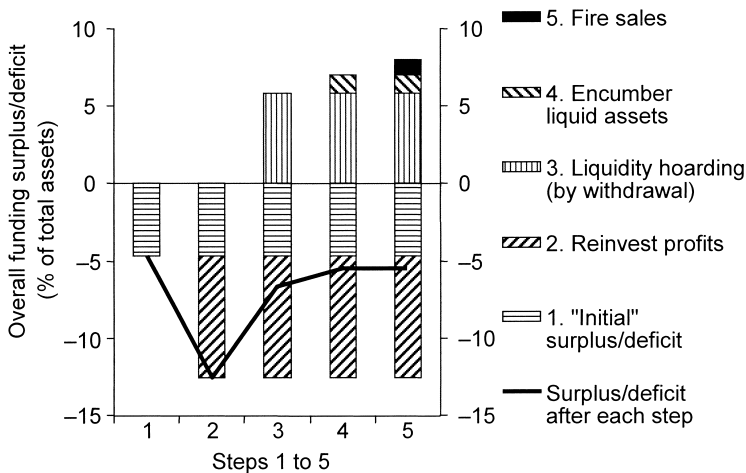
Fig. 1.7   **Steps in flow constraint when wholesale funding withdrawn**

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 selling illiquid assets in a fire sale (option 4). But in this example, the combined effect of these actions is insufficient for the bank to meet its flow constraint and the bank fails.

1.4.3   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 sales and network feedbacks affect other banks' danger zone points scores by weakening their solvency position. If any of the banks reach 25 points as a result, then they suffer snowballing and start to hoard liquidity by shortening maturities, 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.
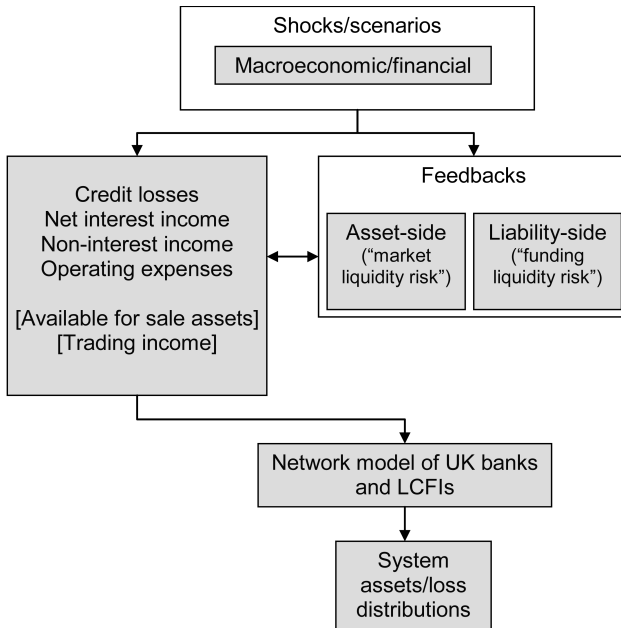
1.4.4   Summary of Systemic Feedback Effects

To summarize, we can see how the framework captures all of the feedback effects depicted in figure 1.1. Confidence contagion is modeled directly within the danger zone scoring system, while liquidity hoarding by shortening maturities is an endogenous response to a weak danger zone score that 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 crystallizes upon default.

1.5   Shocks to Fundamentals and Liquidity Risk: Simulations in RAMSI

So far we have analyzed liquidity risk and associated systemic feedbacks in an isolated fashion. To illustrate the impact of introducing liquidity risk and systemic feedbacks on overall system risk, measured here by the system-wide asset and loss distribution, we now integrate these mechanisms into the RAMSI stress testing model, which simulates banks' profitability from fundamentals. Figure 1.8 provides a high-level overview of RAMSI. We only provide a very brief discussion here—for further details, see Aikman et al. (2009).

A key input into RAMSI are future paths of macroeconomic and financial variables. In the following experiments, these have been generated by a large-scale Bayesian VAR (BVAR). This is the only source of shocks, thereby

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                    ┌─────────────────────────┐
                    │    Shocks/scenarios     │
                    │ ┌─────────────────────┐ │
                    │ │Macroeconomic/financial│ │
                    │ └─────────────────────┘ │
                    └─────────────────────────┘
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Fig. 1.8   RAMSI framework

preserving a one-for-one mapping from macroeconomic variables to default risk (as well as liquidity risk). The credit risk model treats aggregate default probabilities (PDs) and loss given default (LGD) as a function of the macro-economic and financial variables from the BVAR. For most of the loan book, interest income is modeled endogenously. Banks price their loans to households and corporations 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. For other parts of the balance sheet, including all of the liability side, spreads are calibrated based on market rates and other data. On certain liabilities, spreads also depend on the credit rating of the bank in question, which is, in turn, endogenous to its fundamentals. RAMSI also includes simple models for nontrading income and operating expenses, but for simplicity the version used in this chapter assumes that trading income is fixed and excludes portfolio gains and losses on AFS assets. Net profits are then computed as the sum of all sources of income, net of expenses, credit losses, and (when profitable) taxes and dividends.

At this point, we have all the information we need to assess the danger zone score—for example, the projected profit and loss for each bank drives its solvency score and balance sheet characteristics its liquidity scores. We then simulate the sequence of events described in section 1.4. In the absence

of bank failures, or after the feedback loop has completed, we update the balance sheets of profitable surviving banks using a rule of thumb for reinvestment behavior. Banks are assumed to target prespecified 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 its reinvestment funds to meet liquidity needs (step 2 in phase 2).

For the simulations, we use data up to 2007 Q4 (so that all balance sheets are on the basis of end-2007 data) and draw 500 realizations 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 realization is thus driven by a sequence of macroeconomic shocks drawn from a multivariate normal distribution.[16] The results are purely intended to be illustrative rather than being the authors' view of the likely impact on the banks in question.
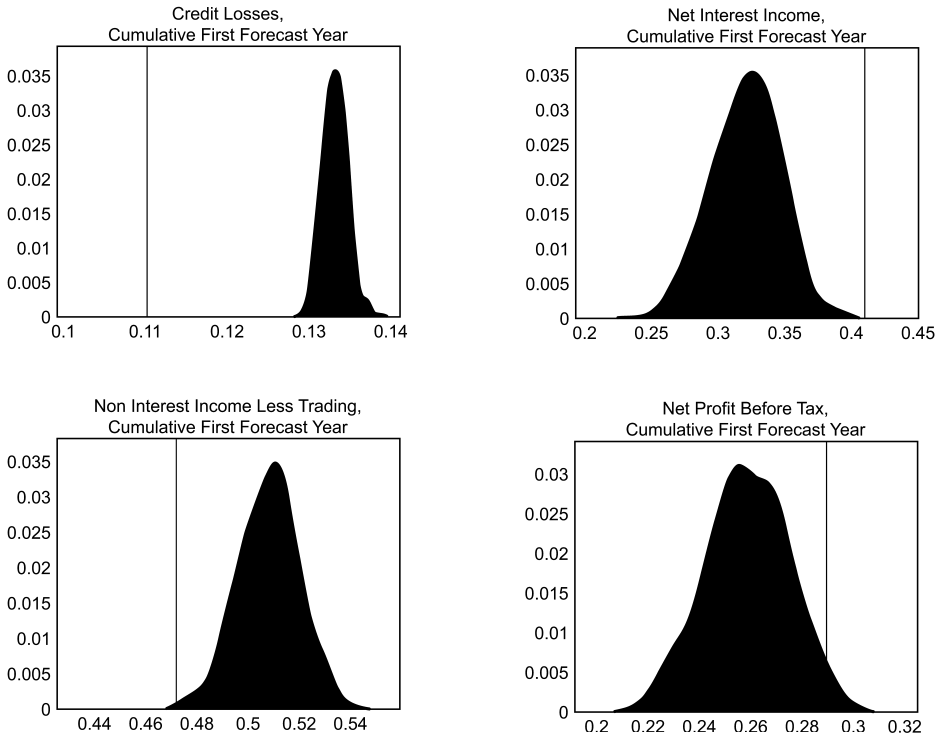
Figure 1.9 shows the simulated distributions of some key profit and loss items, when systemic liquidity feedbacks are not included. For each variable, we calculate aggregate cumulative figures for the first year by adding over banks and quarters, and normalize by aggregate 2007 (beginning of period) capital. The vertical line represents the corresponding figures from the 2007 published accounts, normalized 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 in 2007, reflecting higher funding costs and contractual frictions that prevent banks from instantaneously passing on these costs to their borrowers. The variance of net interest income may be unrealistically high as the version of the model used does not incorporate hedging of interest rate risk.[17] Noninterest income (bottom left-hand panel) remains high, with a median projection above the reported 2007 level; this variable is procyclical but adjusts relatively slowly to macroeconomic changes. The net impact on banks' profitability is summarized in the net profit chart (bottom right-hand panel). As can be seen, profits were projected to be weaker than in 2007.

Figure 1.10 shows the distribution of total assets in the last quarter of the simulation and the average *quarterly* aggregate return on assets (RoA) over the whole three-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

16. In other words, we draw 500 realizations 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.

17. Banks can be penalized under Pillar 2 of Basel II for not hedging interest rate risk in their banking book.

Fig. 1.9   Simulated distributions for profit and loss items: No liquidity effects

Note: In percent of aggregate 2007 capital. Vertical line represents the corresponding figures from the 2007 published accounts, normalized by 2006 capital levels.

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.

Figure 1.11 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 driven by 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. This fat tail emerges in spite of the Gaussian nature of the underlying shocks to macroeconomic fundamentals. These illustrative results point toward the importance of considering funding liquidity risk and systemic feedbacks in quantitative models of systemic risk.
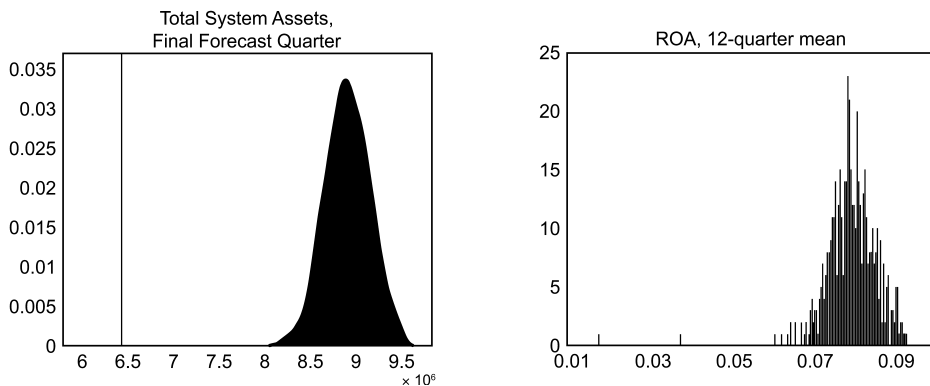
Fig. 1.10   Total system assets—final quarter: No liquidity effects

Note: Vertical line represents total system assets from the 2007 published accounts. RoA on a quarterly basis, in percent.
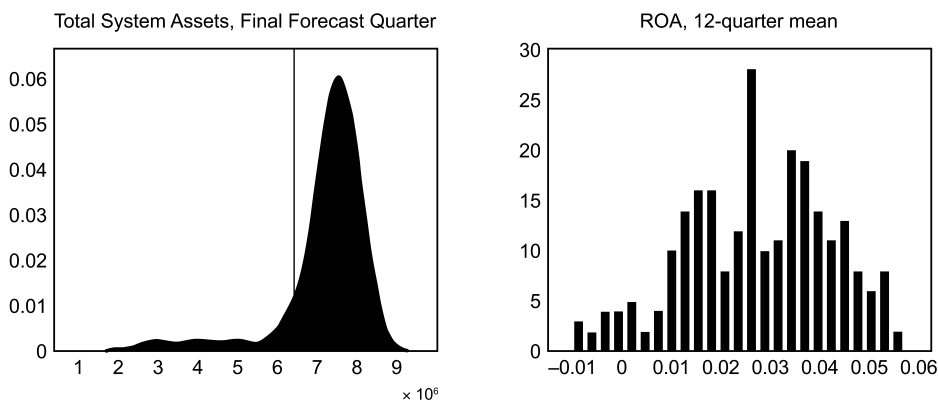
Fig. 1.11   Total system assets—final quarter: With liquidity effects

Note: Vertical line represents total system assets from the 2007 published accounts.

By adding on various components individually, the model can be used to identify how different mechanisms contribute to the profile of systemic risk. For example, the introduction of the danger zone framework permits failure even if a bank's capital does not fall below the regulatory minimum and thus worsens the loss distribution. Confidence contagion, counterparty defaults, liquidity hoarding, and asset fire sales all amplify distress in the tail, but allowing for hoarding and fire sales, increases 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 that tries to disentangle the effects of (post-failure) fire sales and counterparty default, see Alessandri et al. (2009).

1.6   Conclusions and Future Work

The main contribution of this chapter has been to discuss and model how systemic risk may escalate and contagion may spread to other institutions as a bank's funding conditions deteriorate, irrespective of whether the bank ultimately survives or fails. Quantitative simulations illustrate how liquidity feedbacks can amplify other sources of risk.

Our model captures several channels of systemic funding liquidity crises. By using simple indicators and analyzing bank-specific cash flow constraints, 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 asset fire sales may affect the value of other banks' assets, which in turn can affect their 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. It would also be helpful to capture the evolution of systemic liquidity crises on a more granular basis, incorporating more developed behavioral assumptions. 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 modeling the optimal endogenous response to shocks is a highly complex problem—banks would need to optimize over different asset classes and maturity structures, taking account of shocks to fundamentals and behavioral reactions of all other market participants. Finally, it would be interesting to use the framework to explore the role that macroprudential policies such as time-varying liquidity buffers (see Bank of England 2011) might be able to play in containing systemic risk.

Appendix

An Example of a Danger Zone Calibration Using Continental Illinois

Case studies indicate that the danger zone approach performs relatively well, especially in terms of capturing the ranking of institutions under most stress. We have considered case studies beyond the current crisis. An example
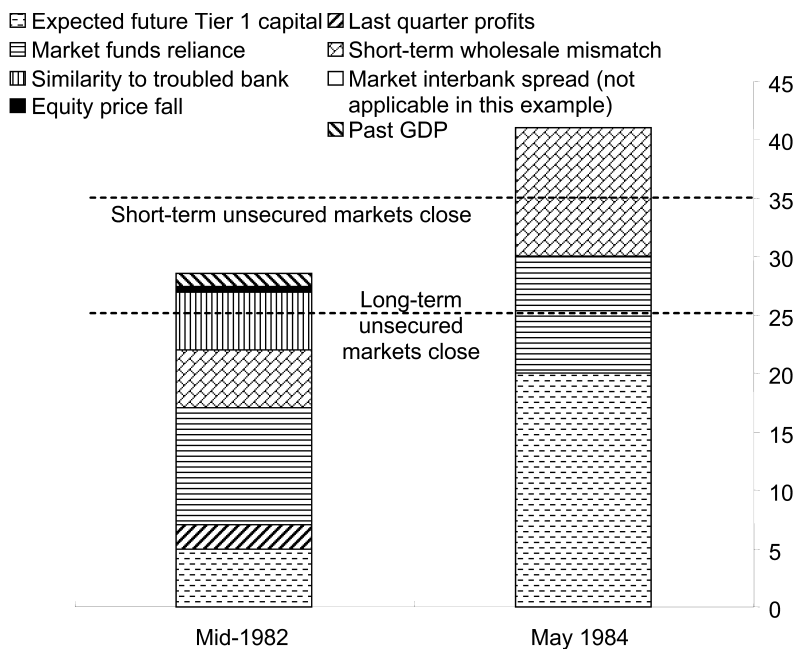
Fig. 1A.1   Applying danger zones to the failure of Continental Illinois

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. Figure 1A.1 scores Continental Illinois in each of these periods.

Reflecting its high dependence on wholesale funding, Continental scores highly 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 that 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 served to increase Continental's DZ score over the next couple of years (the snowballing effect). But the final trigger for the second run was 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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Summary

Let me open by summarizing the main points of the chapter. The chapter describes a liquidity feedback model (hereafter, LFM) within a quantitative