CHAPTER 9

Modeling Correlated Systemic Bank Liquidity Risks

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This chapter proposes and demonstrates a methodology for modeling correlated systemic solvency and liquidity risks for a banking system. Using a forward-looking simulation of many risk factors applied to detailed balance sheets for a 10-bank stylized U.S. banking system, we analyze correlated market and credit risks and estimate the probability that multiple banks will fail or experience liquidity runs simultaneously. Significant systemic risk factors are shown to include financial and economic environment regime shifts to stressful conditions, poor initial loan-credit quality, loan portfolio sector and regional concentrations, bank creditors’ sensitivity to and uncertainties regarding solvency risk, and inadequate capital. Systemic banking system solvency risk is driven by the correlated defaults of many borrowers, other market risks, and interbank defaults. Liquidity runs are modeled as a response to elevated solvency risk and uncertainties and are shown to increase correlated bank failures. Potential bank funding outflows and contractions in lending with significant real economic impacts are estimated. Increases in equity capital levels needed to reduce bank solvency and liquidity risk levels to a target confidence level also are estimated to range from 3 percent to 20 percent of assets. For a future environment that replicates the 1987–2006 volatilities and correlations, we find only a small risk of U.S. bank failures focused on thinly capitalized and regionally concentrated smaller banks. For the 2007–10 financial environment calibration, we find substantially elevated solvency and liquidity risks for all banks and the banking system.

METHOD SUMMARY

Overview
The method provides a valuation of bank on- and off-balance-sheet positions under stress.

Application
The method is particularly useful when a creditor perspective is necessary—a creditor does not care about accounting conventions or about regulatory compliance; the creditor cares about value.

Nature of approach
Monte Carlo simulation; valuation of bank transactions.

Data requirements
Accounting information on capital, loans, and risk-weighted assets. Supervisory data on classified loans and provisions. Information about leverage of corporates and households. Prices that characterize the economic environment (such as interest rates, exchange rates, real estate prices).

Strengths
• The model captures the correlated nature of main risks, such as credit and market risks, overall solvency and liquidity risks, and risks in the interbank market.

Weaknesses
• The model assumes that variables are represented as an n-variate normal distribution and that they have constant trends, volatilities, and correlations. (However, the model could be programmed to allow for stochastic volatilities and correlations.)
• Data intensive.
• For a large number of institutions modeled simultaneously, simulations may take a significant amount of time.

Tool
The Excel spreadsheet macro is not yet available.

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A systemic liquidity shock is an aggregate shortage of liquidity, that is, a situation in which many institutions face liquidity shortages simultaneously, as opposed to one institution suffering a liquidity shortage. Systemic liquidity risk is the probability that this situation takes place. A liquidity shortage can manifest as an inability for institutions to roll over funding (funding liquidity risk), the inability to trade assets at normal bid or ask spreads (market liquidity risk), or, very frequently, both.

The stress test approach developed in this chapter takes the view that absent an aggregate preference shock (i.e., a sudden shift of preferences in favor of higher present consumption) or infrastructure malfunctioning, a systemic liquidity shock is more likely to happen in the presence of a shock to fundamentals that depresses asset values and makes the market reluctant to fund these (suddenly) lower-quality assets or the institutions that hold them. In the presence of incomplete and asymmetric information on the values of assets and the financial condition of banks, this reluctance can also be extended to good assets and solvent institutions.

A systemic liquidity shock is closely associated with the notion of bank panics. Traditionally, there have been two leading alternative views to explain the triggers of panics in the more traditional setting of depositors’ behavior: the random withdrawals theory and the information-based theory. The random withdrawal approach, as developed in Diamond and Dybvig (1983), postulates that a panic is the realization of a bad equilibrium that is due to the fulfillment of depositors’ self-expectations concerning the behavior of other depositors (a pure liquidity shock). Conversely, the information-based approach, as reflected in Allen and Gale (2000), claims that a panic is an episode of market discipline during which depositors attempt to sort among ex ante “good” (solvent) and ex ante “bad” (insolvent) banks in a world of asymmetric information regarding bank asset values. In this context, bank panics can be a normal outcome of business cycles: an economic downturn will reduce the value of bank assets, raising the possibility that banks cannot meet their commitments. Gorton (1988) undertook an empirical study to differentiate between the “sunspot” view and the business-cycle view of banking panics. He found evidence consistent with the view that banking panics are related to the business cycle.

There is also consensus that the global financial crisis has not been a pure liquidity shock but was triggered instead by concerns about the value of bank assets—subprime mortgages and structured products affected by the fall in house prices. Gorton and Metrick (2009) characterized the global crisis as a systemwide “run” in the securitized banking system—more precisely a “run on the repo market”—similar to the banking panics of the 19th century. Both episodes, in their view, were triggered by insolvency problems. They find that during 2007–2008, changes in the London Interbank Offered Rate—Overnight Indexed Swap (LIBOR–OIS) spread, a proxy for counterparty risk in the (interbank) repo market, was strongly correlated with changes in credit spreads and repo rates for securitized bonds. These changes implied higher uncertainty about bank solvency and lower values for repo collateral. They conclude that the market slowly became aware of the risks associated with the subprime market, which then led to doubts about repo collateral and bank solvency. At some point—August 2007—a critical mass of such fears led to the first run on repo, with lenders no longer willing to provide short-term finance at historical spreads and haircuts.

Afonso, Kovner, and Schoar (2010) examined the connections between solvency and liquidity over the global crisis. They tested two hypotheses by which shocks to individual banks can lead to marketwide reductions in liquidity: (1) an increase in counterparty risk, leading to a drying up in liquidity; and (2) liquidity hoarding, that is, banks not willing to lend even to high-quality counterparties in order to keep liquidity for precautionary reasons. Their findings suggest that concerns about counterparty risks played a much larger role than liquidity hoarding. Moreover, in the days after Lehman’s bankruptcy, loan amounts and spreads became more sensitive to borrowers’ characteristics: they observe that large borrowers accessed the federal funds market less after Lehman’s bankruptcy and from fewer counterparties. Furthermore, it was the worst performing large banks (the “bad” banks) that accessed the market least. They do not observe the complete cessation of lending predicted by some theoretical models that focus on liquidity hoarding.

The IMF’s October 2008 Global Financial Stability Report showed that systemic (joint) default risk has been the dominant factor in the explanation of the spreads and that systemic (joint) default risk has influenced the spread since July 2007 (IMF, 2008). It also showed that the repo spread began to present signs of stress in 2005 when the U.S. housing market began its downturn. It then concluded that broadening access to emergency liquidity alone would not resolve bank funding stresses until broader policy measures, including those aimed at the underlying counterparty credit concerns, were implemented.

Consistently, we propose a stress test of systemic liquidity in which systemic liquidity shocks are modeled as a reaction to shocks to asset values resulting from borrower defaults and other factors. In our approach, a liquidity shock (or a “run”) is an extreme episode of “market discipline” by which those providing funding (depositors, wholesale investors, other banks, etc.) attempt to sort among ex ante “good” (solvent) and ex ante “bad” (insolvent) users of funds in a world of asymmetric information regarding asset values. Although the exact timing of a systemic liquidity shock is difficult to forecast, we postulate that they are highly correlated with solvency concerns and contractions in bank lending. Our approach is also consistent with the stress testing literature in which liquidity withdrawals are linked to banks’ solvency risk (Table 9.1).

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1. The risk assessments reported in this analysis were undertaken with the ValueCalc Banking System Risk Modeling Software, copyright FinSoft, Inc.
2. These triggers explain a large portion of the liquidity shortages experienced during the global crisis and were discussed in IMF (2010; e.g., need for centralized repo counterparties, better recording of OTC transactions in repositoriests).
### TABLE 9.1

**Selected Liquidity Stress Testing Frameworks**

<table>
<thead>
<tr>
<th>Framework</th>
<th>Bank of England</th>
<th>De Nederlandsche Bank</th>
<th>Hong Kong Monetary Authority</th>
<th>Proposed Stress Testing Framework</th>
</tr>
</thead>
<tbody>
<tr>
<td>Data</td>
<td>Bank-by-bank financial reporting Bank- by- bank financial reporting Bank- by- bank financial reporting Bank- by- bank financial reporting</td>
<td>Bank-by-bank financial reporting Valuation losses and/or funding withdrawal to selected liquidity items.</td>
<td>Bank-by-bank financial reporting Deposits are withdrawn in line with stressed probability of default (PD) (owing to a loss from asset price declines) of the bank.</td>
<td>Bank-by-bank financial reporting Asset price shocks. Bank liabilities are withdrawn following stressed PD of the bank.</td>
</tr>
<tr>
<td>Origin of liquidity shocks</td>
<td>Funding liquidity shock (cost and access) upon downgrade from solvency shocks (credit and market losses in macro stress testing).</td>
<td>Valuation losses and/or funding withdrawal to selected liquidity items.</td>
<td>Deposits are withdrawn in line with stressed probability of default (PD) (owing to a loss from asset price declines) of the bank.</td>
<td>Deposits are withdrawn following stressed PD of the bank.</td>
</tr>
<tr>
<td>Feedback, spillover, amplification effects</td>
<td>Linear, normal time linkages. Nonlinear effects using subjective but simple scoring system. Second-round effects through impact on asset price upon bank deleveraging and network effects.</td>
<td>Nonlinear effects as banks take deleveraging actions for larger shocks, and they feed back to asset valuation and funding availability (second-round effects).</td>
<td>Deleveraging to restore lost funding is costly owing to distress in asset markets. Interbank contagion (network effects).</td>
<td>Banks attempt to restore net cash flow by selling assets, which affect market liquidity of the assets, further tightening funding liquidity (through higher haircuts).</td>
</tr>
<tr>
<td>Measurement of stress</td>
<td>Various standard metrics (solvency ratio, liquidity ratio, asset value, credit losses, ratings, profit, etc.).</td>
<td>Distribution of liquidity buffer across banks and across severity of shocks.</td>
<td>Probability of cash shortage and default; expected first cash shortage time; expected default time.</td>
<td>Solvency ratio; distributions of net cash flows and equity; joint probability of multiple institutions suffering from simultaneous cash shortfalls.</td>
</tr>
<tr>
<td>Origin of “systemic liquidity” characteristics Pros</td>
<td>Initial macroeconomic shocks and various second-round effects. Nonlinear liquidity shocks and various second-round effects.</td>
<td>From second-round effects.</td>
<td>From initial aggregate shock on asset prices, network effects.</td>
<td>Initial aggregate shock on asset prices and various second-round effects. Nonlinear second-round effects, assess joint probability of liquidity distress, and contribution of individual bank.</td>
</tr>
<tr>
<td>Cons</td>
<td>Includes subjective components to model nonlinearity.</td>
<td>Bank behavioral assumption and feedback effect formulated without strong micro-foundation.</td>
<td>No feedback effects from distress on banks to asset prices.</td>
<td>Bank behavioral assumption and feedback effect formulated without strong micro-foundation.</td>
</tr>
</tbody>
</table>


Note: Bank of England reflects the stress testing framework proposed by Aikman and others (2009); De Nederlandsche Bank reflects the stress testing framework proposed by van den End (2008); and the Hong Kong Monetary Authority reflects the stress testing framework proposed by Wong and Hui (2009).
This chapter also highlights the importance of relating the policy response to the diagnosis of the shock. Systemic liquidity shocks may all look similar, despite their origin (aggregate liquidity-preference-shock infrastructure malfunctioning or solvency concerns). However, the different origin is important to inform the policy response, both preemptively, to minimize the probability of a systemic liquidity crisis, and to manage the crisis, once it happens. For our application to the U.S. banks, we develop a capital surcharge aimed at minimizing the probability that any given bank would experience a destabilizing run. For crisis management, we propose recapitalizing or closing insolvent banks and disclosing enough information to eliminate uncertainties about bank solvency. Liquidity injections by a central bank—that can solve the problem in the case of a change in intertemporal preferences—would likely not be effective if there is reluctance to provide funding for suddenly poor-quality assets. Balance between supply and demand of liquidity would be achieved only by deleveraging, restoring asset quality and confidence, and providing enough information to avoid contagion problems for solvent institutions.

1. Modeling Steps and Data Requirements

A. Modeling Steps

Our approach starts with a detailed solvency stress test for multiple banks and then adds, as an innovation, a systemic liquidity component. It can be used to measure correlated systemic solvency and liquidity risks, assess a bank’s vulnerability to a liquidity shortfall, and develop a capital surcharge aimed at minimizing the probability that any given bank would experience a destabilizing run.

We model three channels for a systemic liquidity event:

- a stressed macro and financial environment leading to a reduction in funding from the unsecured funding markets that is due to a heightened perception of counterparty and default risks;
- a fire sale of assets as stressed banks seek to meet their cash flow obligations. Lower-asset prices affect asset valuations and margin requirements for all banks in the system, and these in turn affect funding costs, profitability, and generate systemic solvency concerns; and
- lower funding liquidity because increased uncertainty over counterparty risk and lower asset valuations induce banks and investors to hoard liquidity, leading to systemic liquidity shortfalls.

The approach proceeds in four stages as illustrated in Figure 9.1: (1) modeling the financial and economic environment; (2) credit risk modeling; (3) systemic solvency risk modeling; and (4) correlated systemic liquidity risk modeling. First, thousands of Monte Carlo simulations are used to simulate correlated changes in many asset prices (foreign exchange rates, interest rates, real estate prices, and market equity indexes), as well as macroeconomic factors that drive bank clients’ defaults (equity values, bank clients’ leverage) between the current time (T0) and a future time (T1). These simulated prices and macroeconomic factors are used to revalue banks’ balance sheets.

A large shock to these prices and macroeconomic factors affect the quality of bank assets directly (higher credit and market risk) and also indirectly through a network of interbank claims. Our model estimates the economic value of banks’ capital, economic capital-to-asset ratios, and bank solvency defaults at T1 and the probability of future solvency defaults at T2 (as measured at T1).

In simulations with higher bank probabilities of default, bank creditors react by showing reluctance to fund bank assets. Confronted with increasing difficulties to roll over their liabilities, banks need to fire sell assets at distressed prices. This in turn aggravates their economic capital-to-asset ratios. At the end of the simulation, the model generates a final distribution of economic capital to asset values as well as a distribution of cash flows. Banks are modeled as failing when their capital-to-asset ratios reach a critical threshold value (2 percent) or in the presence of liquidity shortages. Periods with multiple bank failures are likely to also have multiple banks in weakened financial conditions. This is just the time when losses on interbank credit defaults can lead to correlated banking system solvency and liquidity crises.

B. Data Requirements

The stress test approach has the following intensive data requirements. In some cases, it may be possible to substitute expert opinion for data that may not be available.

- Time series related to the financial and economic environment in which banks operate. These series need to be of sufficient length to allow trends, volatilities, and correlations to be estimated during both “normal” and “stress” periods. The following data are of interest:
  - short-term domestic and foreign interest rates and their term structures
  - interest rate spreads for loans of various credit qualities (securities)
  - foreign exchange rates (as relevant)
  - economic indicators (GDP, consumer price index, unemployment, and so on)
  - commodity prices (oil, gold, and so on)
  - sector equity indices
  - regional real estate prices

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3 An interesting reflection about the policy response to the global crisis and the importance of relating the diagnosis to the policy response can be found in Taylor (2008).

4 To the extent that a central bank provides liquidity in exchange for a trouble asset, liquidity injections can work because it would allow the bank to deleverage—by getting rid of the trouble asset.
• Information on banks’ assets, liabilities, and, ideally, off-balance-sheet transactions, including hedges, such as
  – various categories of loans, including information about their credit quality, maturity structure, and currencies of denomination
  – currency and maturity structure of the other assets and liabilities
• Information to enable calibration of behavioral relationships, such as
  – capital as well as operating expenses and tax rates
  – clients’ leverage ratios and recovery rates, to be able to calibrate credit risk models
  – interbank exposures, including bilateral credit exposures among the various banks
2. MODEL CALIBRATION TO THE U.S. FINANCIAL ENVIRONMENT AND THE U.S. BANKING SYSTEM

For the characterization of the U.S. financial and economic environment, we use a set of variables, including interest rates, interest rate spreads, foreign exchange rates, U.S. economic indicators, global equity indices, 14 Standard and Poor's (S&P) sector equity returns, and 20 Case-Shiller regional real estate price returns. The Financial and Economic Environment Model is calibrated for two different “regimes.” The first calibration is based on data from the 20-year period 1987–2006. The second calibration is based on data from the period 2007–10.

Using Call Report Data,5 we constructed 10 stylized U.S. banks in four categories: two megabanks that aggregate the assets and liabilities of two groups of banks, with higher and lower equity capital-to-asset ratios and assets above $500 billion; three large banks that aggregate the assets and liabilities of groups of banks with assets between $100 billion and $500 billion; three medium-sized banks that aggregate groups of banks with assets between $10 billion and $100 billion; and two small banks that aggregate groups of banks with assets below $10 billion. The various banks are sized so that they have an appropriate weighting relative to the overall U.S. banking system. For example, the megabanks have approximately 62 percent of the total assets for the model banking system. A larger or smaller number of banks could be modeled.

Sector and regional concentrations of bank loan portfolios are also a significant risk factor. The smaller banks are modeled as making mortgage loans in one or two states (e.g., California, or Florida and Georgia) and three sectors of the economy (industrial, retail, and services). Medium-sized banks are modeled as lending in larger regions (West Coast, Mid-America, or East Coast) and four sectors of the economy. Large and megabanks are modeled as lending nationally in 20 regions and 14 sectors of the economy.

Systemic solvency risk in our model depends on bank exposure to borrower creditworthiness (credit risk), including credit concentration, as well as correlated market prices (market risk). The risk assessment horizon was set at one year. The model is flexible to accommodate other risk modeling time steps.

3. CREDIT RISK MODELING

Business and mortgage loan credit risk assessments are based on simulations of business debt-to-value ratios and property loan-to-value ratios using a contingent claims type model.6 The future values of companies are systematically related to simulated sector-equity returns plus a company-specific random return. When business debt-to-value ratios cross critical boundaries, the credit rating of the loans is assumed to change. At identified high debt-to-value ratios, the loans are assumed to default.7 In this study, we use the U.S. business credit risk model estimated by Barnhill and Maxwell (2002). Correlated variations in recovery rates on business loans are also an important systematic risk factor. In our analysis, recovery rates on business loans are modeled as increasing (decreasing) as stock market returns increase (decrease).8

A. Corporate loan portfolio modeling

Given that we did not have information on the credit quality of corporate borrowers for each bank, we assumed that initially, the set of business loans in U.S. bank portfolios have the same credit quality distribution for all banks and that this distribution is the one described in the Shared National Credits Review issued annually by the Board of Governors of the Federal Reserve System, Federal Deposit Insurance Corporation (FDIC), Office of the Comptroller of the Currency, and Office of Thrift Supervision.9 Foreign corporate loans are modeled following the same credit risk analysis procedures used for domestic loans. However, we do account for foreign exchange rate risk. For those assets and liabilities where credit risk is not modeled, valuation is based on a present value approach where the cash flows are discounted using the simulated interest rates of a selected term structure and the simulated values for the correlated exchange rates, in the case of securities denominated in foreign currency.

B. Individual loan portfolio modeling

Given the lack of an alternative model, loans to individuals were modeled entirely as a portfolio of mortgage loans. This approach has obvious limitations but does capture any correlations among the default rates on other loans to individual and mortgage loans resulting from unemployment rates, low property prices, and so on. The initial loan-to-value ratios for mortgage loans were estimated from data given in Fannie Mae’s and Freddie Mac’s annual report plus esti-

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5 We assumed that the reported balance sheets represent reasonable estimates of current market values for bank assets and liabilities.

6 See Black and Scholes (1973) and Merton (1973).

7 For a more detailed discussion, see Barnhill and Maxwell (2002), Barnhill, Papapanagiotou, and Schumacher (2002), and Barnhill and Souto (2009).

8 See Cantor and Varma (2005).

9 In the U.S. bank calibration of our model, loans classified as “substandard,” “doubtful,” and “loss” were modeled as having a credit risk similar to B, C, and D rated bonds. The balance of the business loan portfolio was divided evenly between the A, BBB, and BB rating categories.
mates of the likely distributions of mortgage portfolio loan-to-value (LTV) ratios based on assumed initial LTV ratios and trends in national real estate prices.

In our model, the future values of properties are systematically related to regional real estate returns plus a property-specific random term. The probability of a mortgage loan defaulting is modeled as being related to its LTV ratio. For LTV ratios between 1.2 and 1.4, the default rate is set at 20 percent. For LTV ratios between 1.4 and 1.6, the default rate is set at 40 percent. For LTV ratios between 1.6 and 1.8, the default rate is set at 60 percent. For LTV ratios over 1.8, the default rate is set at 80 percent. Recovery rates on mortgage loans are correlated with real estate prices and are assumed to be the LTV ratio less a 30 percent liquidation cost.

Correlated changes in the values of real estate assets by region and business assets by sector are driven by the correlated returns on regional real estate indices and sector equity indices in the financial and economic environment. Correlated default rates on mortgage loans in various regions and business loans in various sectors are driven by the assumed initial LTV ratios and correlated changes in the values of the real estate and business assets securing the bank loans. Such correlated defaults on bank loan portfolios produce correlated banking-system systemic solvency and liquidity risks.

4. LOAN PORTFOLIO CONCENTRATION MODELING

The concentration of bank loans in various sectors (e.g., energy), regions (e.g., Florida), and security types (e.g., mortgage loans) are particularly significant bank risk factors that are often not modeled adequately. To account for loan portfolio concentration risk, we model the correlated market and credit risk on 200 business loans distributed across up to 20 sectors of an economy and 200 mortgage loans distributed across up to 20 regions of a country. We find this to be an adequate number of loans, sectors, and regions to statistically distinguish between more concentrated and more diversified portfolios. More sectors, regions, and loans could be modeled.

We also model correlated market risk for approximately 100 other bank assets and liabilities.

5. SYSTEMIC SOLVENCY RISK MODELING

One of the outcomes of the risk assessments of the financial and economic environment and bank portfolios after many simulation runs is joint distributions of each of the 10 banks’ market value of equity capital at T1.

\[ MVE_t = \sum_{i=1}^{n} A_{i,t} = \sum_{i=1}^{n} L_{i,t}, \]

where \( MVE_t \) is the simulated market value of the bank’s equity at time \( t \); \( A_{i,t} \) is the simulated market value of the \( i \)th asset at time \( t \), which reflects the simulated financial environment variables (e.g., interest rates, exchange rates, equity prices, real estate prices) and, where appropriate, the simulated credit rating of the borrower; and \( L_{i,t} \) is the simulated market value of the \( i \)th liability at time \( t \), which reflects the simulated financial environment variables (e.g., interest rates, exchange rates). The bank’s asset and liability levels are also adjusted to reflect bank net interest income, fee income plus other income less operating expenses, and taxes over the simulation period.

After many simulation runs, joint distributions of the various banks’ capital-to-asset ratios are estimated and used to assess bank defaults and systemic banking system solvency risks at T1.

\[ Capital\_Ratio_t = MVE_t / \sum_{i=1}^{n} A_{i,t}. \]

For each run of the simulation, the simulated capital ratio is also used to estimate each bank’s correlated probability of defaulting at T2. These future default probabilities are derived under the assumption that the distribution of changes in capital ratios between T1 and T2 is identical to the distribution of changes in capital ratios between T0 and T1.

During times of economic stress, it is likely that default losses on loans will increase, and many banks will either fail or be weakened significantly, particularly if they have similar asset and liability structures. This is just the time when the failure of several banks could, through interbank credit defaults, precipitate a number of simultaneous bank failures. Interbank credit risk is modeled using a network methodology. Given that we do not have precise information on interbank borrowers’ and lenders’ identities, we assumed that the amount of interbank loans made between each bank is proportional to their total interbank borrowing and lending.

In the current study, and consistent with current U.S. regulations, we model a bank as failing when its ratio of equity capital-to-assets falls below 2 percent. In this case, the bank becomes incapable of honoring its interbank obligations and defaults on them. The recovery rate on defaulted interbank obligations is assumed to be 40 percent. Such losses could affect counterparty banks’ capital ratios and potentially lead to additional bank failures. A network methodology is applied repeatedly until no additional banks fail, after which the probability of multiple simultaneous bank failures (i.e., systemic solvency risk) can be computed. The outcome of this step is again equity-to-asset ratios and bank

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10 See Bhutta, Dokko, and Shan (2010).

11 The FDIC Improvement Act of 1991’s Prompt Corrective Action provision states that a bank should be closed when its tangible capitalization reaches 2 percent. The trigger point for bank failure could be set in the stress test framework model at any relevant regulatory level, including the new leverage ratio as proposed under Basel III.

12 In the current study, precise information on interbank borrowers’ and lenders’ identities are unavailable; hence, the amount of interbank loans made between each bank is assumed to be proportional to their total interbank borrowing and lending.
failures for T1—that includes losses due to defaults on interbank claims—and a probability of default for each bank at T2 (estimated as discussed in the previous paragraph) for each run of the simulation.

6. MODELING CORRELATED SYSTEMIC LIQUIDITY RISK

A primary contribution of the model to stress testing is the addition of correlated liquidity runs on banks, driven by heightened risks or uncertainties, regarding future bank solvency. Changes in bank liabilities observed over the period from 2007 to the first quarter of 2010 were used to develop an estimated relationship between a bank’s probability of default and the rate of withdrawal of total liabilities over the period T1 to T2.

Bank liquidity outflows are estimated under two cases. In Case 1, total liability withdrawal rates match those experienced by bank holding companies (BHCs) with elevated default probabilities during the 2007–10 period. In Case 2, higher total liability withdrawal rates match those experienced by investment banks; because investment banks have a very low level of insured deposits, this case provides a way to calibrate a more stressed scenario where funding sources may dry up very quickly. In Case 2, for lower default probabilities we modeled potential reductions in specific liability accounts (e.g., demand deposits, time deposits, jumbo time deposits, federal funds, repos), which reflect actual liability structures of the stylized BHCs.

Because of incomplete information on particular banks, we assume that bank creditors are also aware of and react to developments in the overall banking system. We thus model systemwide weighted average banking system default probabilities and assume that they have some impact on liquidity runs. In particular, liquidity runs for a particular bank are modeled as being driven by the probability of failure for that bank at T2 plus a factor equal to 10 percent of the systemwide weighted average default probability (i.e., the adjusted probability of failure). Table 9.2 summarizes assumptions on total liability withdrawal rates associated with different default probability ranges for each case.

Banks that face a liquidity run are assumed to follow one of two strategies. In the first strategy, banks stop lending in the interbank and repo markets, liquidate interest-bearing bank deposits, sell government securities, and sell other securities. If these steps do not produce adequate liquidity, they ultimately default on their obligations. In the second strategy, banks sell their liquid securities and reduce their loan portfolios in proportions similar to that observed in U.S. BHCs having elevated failure probabilities.

Banks pay a high cost when they are forced to sell assets during periods of extreme financial market stress. We model bank losses resulting from the fire sale of assets. This cost is given by a selling price with an embedded high liquidity premium and consequently well below its fundamental price. In this way, the model captures the interaction between funding and market liquidity and the second-round feedback between solvency and liquidity risks. Developments in bid-ask spreads in several securities markets during the 2000–2009 period were used as a proxy for fire sale prices. At the peak of the crisis (September 2008), the size of the bid-ask spread was in the 5–10 percent range across different asset qualities, suggesting a discount factor of 3–5 percent to represent the loss suffered by the bank under distress when forced to liquidate assets. These values are in line with Duffie, Gârleanu, and Pedersen (2006), Coval and Stafford (2007), and Aikman and others (2009).

7. RESULTS

In the 2007–10:Q1 financial environment under Case 1 (BHC withdrawal rate), the probability that about 3 out of...
10 banks will simultaneously find themselves unable to make payments (i.e., have a negative cash flow) is 3.8 percent (Table 9.3). That is, the risk of a systemic liquidity shock for this hypothetical U.S. banking system as of June 2010 would be low. In this example, the smaller banks are more affected than the larger ones because of their higher credit risk concentration and exposure to the macro risk factors that triggered the recent crisis. In addition, although banking failures occurred among smaller banks, their liquidity shortages did not lead to a systemic liquidity crisis. In the 2007–10:Q1 financial environment under Case 2 (investment bank withdrawal rate), the probability that 3 out of 10 banks suffer a liquidity shortage increases to 12.7 percent.

Such potential liquidity shortages can create pressures for substantial reductions in bank lending and thus affect the real economy. Indeed, both liquidity shortages and reductions in bank lending were observed during the global crisis. In Case 1, if the stylized banks facing liquidity runs reduce both securities and loan portfolios, the impact on total loans would be small (Figure 9.2, left panel, vertical axis). In Case 2, by contrast, a potential liquidity run could lead to a significant reduction in total loans, of up to 43 percent, although with a low probability of less than 1 percent attached to this event (Figure 9.2, right panel, horizontal axis).

These stress test results generally show that the ability of banks to weather a financial and economic shock, and its impact on solvency and liquidity depends on a number of factors, including (1) the size of the shock; (2) the adequacy of capital; (3) the availability of liquid assets; and (4) the exposure to short-term wholesale liabilities (in this model, interbank exposures). In this framework, if institutions were sufficiently capitalized and, hence, able to sell liquid assets and deleverage in an orderly manner, then there would be no systemic liquidity shock.

The methodology can be used to estimate an additional required capital surcharge or buffer to reduce the risk of future liquidity runs by lowering bank default risk. Using the distribution of capital ratio changes, the methodology can estimate the additional capital buffer required to reduce the probability of a bank experiencing a liquidity run over the next year to below 10 percent at a 99 percent confidence level (see Table 9.4). Of the 10 stylized banks, the small banks need to add the most capital because of their undiversified asset exposures to regional real estate sectors, where credit losses have been the highest.

### 8. CONCLUSION

Systemic banking system risks were poorly understood and managed prior to the current crises. We propose and demonstrate a forward-looking simulation methodology applied to the financial and economic environment and detailed balance sheets for a 10-bank model banking system. The model estimates the magnitude and probability of correlated solvency and liquidity risks that affect bank borrowers, banks, the banking system, and the real economy.

In our model, banks fail from a solvency perspective when their simulated capital ratios fall below some critical level (e.g., 2 percent). Banks experience liquidity problems when their risk of future insolvency or the banking system’s overall risk of insolvency rises to an unacceptable level (e.g., 10 percent). Correlated systemic risks materialize when multiple banks become insolvent or face liquidity risks simultaneously. Systemic risks are driven in part by large adverse regime shifts in the financial and economic environment that

### TABLE 9.3

<table>
<thead>
<tr>
<th>Number of banks</th>
<th>Probability Case 1</th>
<th>Probability Case 2</th>
</tr>
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<tbody>
<tr>
<td>1</td>
<td>98.49</td>
<td>98.49</td>
</tr>
<tr>
<td>2</td>
<td>20.28</td>
<td>23.68</td>
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<tr>
<td>3</td>
<td>3.77</td>
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<td>4</td>
<td>1.60</td>
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<tr>
<td>5</td>
<td>1.13</td>
<td>1.98</td>
</tr>
<tr>
<td>6</td>
<td>0.75</td>
<td>1.51</td>
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<td>7</td>
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<td>9</td>
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</tr>
<tr>
<td>10</td>
<td>0.00</td>
<td>0.09</td>
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</table>

Sources: Authors; and SNL Financial.

### Figure 9.2

Total Loan Reductions

Sources: Authors; and SNL Financial.

Note: The right panel shows the results of the left panel with a finer set of x-axis losses of loans and lower probability (y-axis).
catch many entities by surprise. Such economic shocks drive down the value of large asset classes (e.g., real estate and businesses), resulting in dramatically higher default rates and loss rates on loans for many banks simultaneously. Banks experiencing funding outflows are likely to contract lending with significant potential impacts on the real economy.

In our model, bank solvency and liquidity risks also are driven by asset and liability structures, loan credit quality, sector and regional loan concentrations, and equity capital levels, all of which can be changed by bank managers and affected by bank regulators. Such potential systemic risks may materialize only in the context of very adverse financial and economic regime shifts that may occur only infrequently (but have extreme impacts).

Through the interbank lending market, bank failures may impose additional losses on otherwise solvent banks that cause them to also fail or increase their probability of failing, thus further increasing systemic risk levels. We find high correlations between insolvencies in megasized banks and incremental insolvencies of other banks throughout the banking system, which increases systemic risk.

Insufficient liquid assets that prevent an otherwise orderly “asset shrinking” to offset reductions in funding may also be a significant risk factor. The forced sale of assets at “fire sale” prices may also affect banks’ correlated solvency and liquidity risks.

The model was calibrated with publicly available data on the U.S. financial and economic environment and the U.S. banking system. For the 1987–2006 financial environment calibration, we find only a small risk of bank failures focused on thinly capitalized and regionally concentrated smaller banks. We find no likelihood of systemic solvency or systemic liquidity risks. For the 2007–2010 financial environment calibration, we find substantially elevated solvency and liquidity risks for all banks and the banking system. When potential interbank default losses and liquidity runs are modeled, 7 of the 10 banks (including one megabank) fail at the same time with a 1 percent probability.

Within our model, we can estimate the current bank equity capital levels that are needed to reduce bank solvency and liquidity risk levels to an agreed target at a given confidence level. We conclude that substantial additional equity capital (e.g., 3 percent to 20 percent of assets) is needed to minimize potential solvency and liquidity risks. We can also assess the bank and systemic banking system impacts of changes in the other identified risk variables.

Important areas for future research on correlated solvency and liquidity risk include assessing (1) the relationship between systemwide stress levels and liquidity risk for individual banks; (2) correlated changes in all liability accounts for banks with elevated solvency risk; (3) how volatility in bank loan collateral values increases bank solvency and liquidity risk; (4) correlations between the volume of repossessed collateral (e.g., real estate), subsequent price declines for that asset type, and subsequent default rates on related bank loans; and (5) correlated sovereign risk. Modeling potential economic regime shifts is also an exceptionally important risk assessment topic.

REFERENCES


<table>
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<tr>
<th>TABLE 9.4</th>
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<td><strong>Initial capital ratios</strong></td>
<td><strong>Approximate additional equity capital required at T0 to have 1% probability of a 10% probability of failure at T1</strong></td>
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Source: ValueCalc estimates.


