Financial Stability, Monetary Policy, and Central Banking

Rodrigo A. Alfaro
editor

Central Bank of Chile / Banco Central de Chile

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Financial Stability, Monetary Policy, and Central Banking: An Overview

Rodrigo A. Alfaro
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The financial developments of the last decade had a large impact on the management of risk, providing more diversified portfolios to investors. Based on these complex financial contracts, investors were able to shift the investment possibilities frontier outward; however, that movement generated intricate networks. At the same time, global financial integration increased significantly, facilitating the propagation and expansion of financial shocks.

The recent financial crisis is evidence of such networking sensitivity. In February 2007, Freddie Mac announced its intention to reduce its mortgage portfolio risk by ceasing to purchase risky loans, and then in April of the same year, one of the leading companies in the subprime mortgage market declared bankruptcy. The two events foretold the ending of the housing boom in the U.S. economy and later exposed its financial fragility. In the following year, other U.S. companies related to the housing sector also declared bankruptcy. Meanwhile, the story in Europe was not too different. In September, Northern Rock was authorized additional liquidity provision by the Bank of England, consolidating the idea of a housing bubble that was transversal to developed economies.

The propagation of the mortgage crisis to other financial institutions was fueled by the use of securitized packages, which could be swept away from balance sheet reports, generating a

This introduction and the papers in this volume were submitted in March 2009, and thus reflect developments that had taken place up to that date.

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false reduction in credit risk. These packages were outstandingly attractive to other investors, for they were classified as low risk by professional ratings agencies, while enjoying low financing costs during the long period of expansive monetary policy. The mortgage crisis thus mushroomed into a global financial crisis, and the associated financial instruments came to be labeled as toxic and, given their inherent complexity, were difficult to price in the face of falling underlying prices.

The closure of financial intermediaries linked to the mortgage sector affected financial institutions, with a potentially systemic impact. This motivated the U.S. Federal Reserve and the U.S. Treasury to undertake extraordinary actions, such as the provision of credit facilities for the acquisition of Bear Stearns by J.P. Morgan and the expansion of credit lines to Fannie Mae and Freddie Mac. The Federal Reserve also widened the list of acceptable collateral for liquidity provision. By mid-September, a new financial event shook all fragility indexes: Lehman Brothers declared bankruptcy. This event resulted in a crisis of confidence and the drying up of the interbank market for liquidity, mainly driven by the uncertainty about the liquidity and solvency of the involved parties. In the aftermath, the Federal Reserve provided generous funding to the insurance company American International Group (AIG) to ensure the continuity of its operation. Given AIG's intricate network of operations, its eventual fall would have resulted in a systemic liquidity problem. Afterward, both the Federal Reserve and the Treasury generated a recovery plan for the banking sector, which has been replicated by other industrial economies.

This crisis opened the debate on macroprudential policies and the role of monetary and international authorities. Thorough analysis of these policies implies assessing early alert indicators, the information on which these are based, and their properties. Likewise, the quantification of the systemic importance of any given financial institution allows informed choice among alternative policy actions. The assessment of these features allows improvements in the supervision framework governing financial institutions, which enables authorities to deal with a crisis in a timely and efficient manner.

The Twelfth Annual Conference of the Central Bank of Chile, "Financial Stability, Monetary Policy, and Central Banking," held in Santiago on 6–7 November 2008, provided the occasion to discuss early warning indicators, with the subprime crisis in the background. This conference presented theoretical and

empirical research in both risk analysis by financial institutions and the network effects in financial markets. It also provided the opportunity to sketch these tools in the context of financial crises, thereby generating a critique on the potential weaknesses of current regulation. This overview summarizes the main topics discussed at the conference.

1. Risk Assessment

Financial institutions must maintain a fragile balance between risk taking, stemming from multiple investment decisions, and adequate capital provisions that guarantee enough buffer to face previous commitments with demand depositors. Specifically, in the case of banks, regulators acknowledge that the riskiest operation in the banking business is also the oldest: loan provision. The risk stems from the unilateral reneging of the debtor. A second risk source is market risk, which consists in the deterioration of one's net position in a given unit of account, such as stock options, currency, or interest-bearing assets. Market risk and operational risk are regulated through the first pillar of the Basel II agreement, which covers minimum capital requirements based on risks measured from standardized methods or internally generated processes.

Credit risk analysis requires a statistical structure. Merton (1974) highlights the importance of default probabilities. His work assumes that a firm has risky assets, so that its market value corresponds to the value of a purchase option whose exercise price is the institution's debt burden valued at the risk-free rate. This model provides a method for extracting asset market values and their volatilities (Duffie and Wang, 2004). Alternatively, Crouhy, Galai, and Mark (2000) use Ito's lemma to relate asset volatilities with a firm's market value volatility, forming a system of nonlinear equations to obtain the market value of assets and their volatility.[1] One relevant statistic in this setup is distance to distress, which is the number of standard deviations that the asset value is above the debt value. Under Merton's (1974) model, default probability is

1. Byström (2007) presents a simplified distance to distress, in which (i) the trend factor is small and (ii) default probability is close to zero. Under these assumptions, distance to distress is defined by the firm's leverage and its market value volatility, so it can be obtained directly from balance sheets and market information without resorting to a system of equations.

computed using the cumulative normal distribution of the negative distance to distress.

Because the model is based on option values, it has been labeled contingent claims analysis (CCA) and has been used successfully at the institutional level (Duffie and Wang, 2004). In contrast, option pricing requires that the default probability derived from the distance to distress be calculated under a risk-neutrality assumption.[2]

Additionally, Crosbie (2001) modifies distance to distress so that the resulting default probability mimics the historical distribution of default. For this purpose, he uses the Sharpe quotient to correct the trend effect and employs more general density functions than the normal distribution. These measures are commercialized by Moody's KMV under the name of expected default frequencies (EDF). They have been successful in predicting firm insolvency and real variables (Gilchrist, Yankov, and Zakrajsek, 2008).

In this volume, Dale Gray, Robert Merton, and Zvi Bodie discuss how to extend CCA for different economic sectors, including the corporate, financial, household, and sovereign (government and monetary authorities) sectors. The authors outline the relevant risk transfers and then use these to elaborate a procedure for developing macroeconomic stress tests that affect financial stability, defined by the solvency of the banking system. Gray and Malone (2008) develop the CCA model using the cases of Thailand during the Asian crisis and Brazil in 2002. Blavy and Souto (2009) use banks' EDFs to establish a macro-financial model for the Mexican banking system. They find a strong relation between domestic interest rates and EDFs, which also provide an early warning for financial instability. For Chile, Dale Gray, Carlos García, Leonardo Luna, and Jorge Restrepo develop a small dynamic macroeconomic model that includes the distance to default of the banking system. The authors confirm that the dynamic and nonlinear elements of their model result in more persistent shock trajectories than those stemming from traditional vector autoregression (VAR) models.[3] They also

2. Because the risk-free rate is lower than asset returns, this probability should be adjusted to better reflect the distance to distress. Zurita (2008) uses this methodology for forecasting bankruptcies among Chilean businesses. He finds that CCA delivers much higher bankruptcy probabilities than those empirically observed.

3. Similar results are found by Alfaro, Calvo, and Oda (2009), who consider the dynamics of banking aggregates in a nonlinear VAR. Misina and Tessier (2008) consider that a fundamental issue in stress-test models is their nonlinear component, which better captures the dynamics of extreme events.

explore the consequences for output and inflation volatilities (and their trade-off) when the Taylor rule considers systemic risk through distance-to-distress deviations. Using simulations, they conclude that the central bank's consideration of distance-to-distress deviations reduces both inflation and output volatilities.

A micro-oriented approach is presented by Marcelo Fuenzalida and Jaime Ruiz-Tagle, who assess household financial risk using data from the Social Protection Survey (Encuesta de Protección Social, or EPS) and the Household Financial Survey (Encuesta Financiera de Hogares, or EFH). The EPS contains historical labor-related data on individuals who are active in the labor market, for each surveyed household. Using this information, the authors model unemployment duration to characterize labor income, which is the main source of financial risk at the household level. Their results show that the higher the attained educational level, the lower the probability of becoming unemployed. The EFH is conducted by the Central Bank of Chile and is based on a similar survey conducted by the Bank of Spain (Bover, 2004). Its aim is to characterize Chilean household debt, which translates into an oversampling of households in higher income quintiles and motivates the inclusion of extensive detail in the survey section relating to debt. Using the results from the unemployment duration section, Fuenzalida and Ruiz-Tagle simulate financial stress tests on the surveyed households. They consider as risky those households whose financial-burden-to-income ratio is above 75 percent, and whose expenditure level is above 20 percent of total household income. Under this definition, 9.5 percent of surveyed households are risky, and they account for 16 percent of the total debt documented in the survey. Stress test exercises also show that a rise in the unemployment rate generates a less-than-proportional increase of total household debt at risk.

2. Network Effects

A second element in risk analysis is the existence of network effects among involved financial institutions. These could be the outcome of financial and real factors. In the first category, we include the spillover effects generated between financial markets that had given rise to the literature on financial contagion well before the crisis. Statistical measures of financial contagion have been developed in the seminal work of King and Wadhwani (1990), who also explore its statistical implications for stock markets. In

the same line, Forbes and Rigobon (2002) propose the concept of contagion as a force that is exogenous to the inherent dynamics of financial markets.

In this volume, Francis Diebold and Kamil Yilmaz use the variance decomposition of a VAR model to capture the spillover effects that were observed in stock markets in Argentina, Brazil, Chile, Mexico, and the United States. They use this index to identify the main episodes of turbulence from 1994 to 2008. Their results show that the current financial crisis displays similar features to the Asian and Mexican crises. Beirne and others (2008) present statistical evidence on the increase of spillover effects during periods of financial turbulence. This is consistent with the empirical evidence that spillover effects run from developed economies to emerging economies during these periods of stress, and because emerging economies tend to be financially weaker, they are more prone to display higher volatility.

In terms of network contagion analysis, Prasanna Gai and Sujit Kapadia present a network model in which it is possible to separate the network contagion probability from its potential systemic impact. The authors discuss the observation by Cifuentes, Ferrucci, and Shin (2005) that the higher the connectivity of a network, the higher its capacity to absorb shocks, but at the same time, the more channels through which the shock can be transmitted. Under some of the scenarios studied, the total effect on the system is higher than would be the case with lower connectivity. In a different paper, David Aikman, Piergiorgio Alessandri, Bruno Eklund, Prasanna Gai, Sujit Kapadia, Elizabeth Martin, Nada Mora, Gabriel Sterne, and Matthew Willison present the RAMSI Project, which adds financing liquidity risk to a model of credit risk and valuation contagion. In particular, the project proposes a criterion to incorporate diverse information from financial institutions' balance sheets and from the market to determine intermediaries' access to market funding. The model represents an important advance in the available toolkit for stress test exercises on the financial system.[4]

Interdependencies among lenders have a strong impact on the credit risk of asset portfolios. Vasicek (1987) presents a simple solution to correct default probabilities under an atomized portfolio. The model assumes that the standardized returns of each asset can be

4. Jara, Luna, and Oda (2008) present a discussion on risk scenarios for the Chilean banking industry.

explained by a common factor and an idiosyncratic one. It then uses the average correlation between asset returns to correct the default probability. Crouhy, Galai, and Mark (2005) discuss the applicability of the credit-risk model proposed in Basel II, according to which it is possible to establish capital requirements for classes of loans.

Alternatively, copula models have been used in the joint modeling of asset risk (Cherubini, Luciano, and Vecchiato, 2004; Li, 2000). Copulas allow the generation of joint distribution functions based on the univariate distribution of each asset and on measures of their codependencies. Risk analysis can then be undertaken in a two step procedure: first, for every loan or institution, and, second, for the whole portfolio or related system. Copulas thus possess twice as many degrees of freedom, as the analyst may choose to work with several different univariate distribution functions and then obtain multivariate analysis based on different copulas.

Miguel Segoviano and Charles Goodhart present a paper on measuring financial stability in the U.S. banking system. They use univariate measures obtained from the market prices of banks' credit default swaps (CDSs) and a nonparametric copula (CIMDO) that collapses this information at the bank level on a maximum entropy basis. They use the CDSs to extract information on the default probability under risk neutrality, obtaining superior information to the EDFs when derivatives markets are developed. Singh and Spackman (2009) propose using these measures in combination with stochastic recovery rates, which would provide more adequate signals during episodes of stress. Additionally, CIMDO has advantages over parametric copulas, in that it does not require the parameterization of banks' default dependence measures, such as the Kendall or Spearman coefficients.

Finally, macroeconomic theory incorporates financial frictions into risk analysis, through extensions to general equilibrium models. Bernanke, Gertler, and Gilchrist (1999) present a model where firms face external financing costs that are above the risk-free rate. This difference can be traced to the firm's agency cost of generating a credit contract. The paper by Ethan Cohen-Cole and Enrique Martínez-García extends the Bernanke-Gertler-Gilchrist model to include banks' capital adequacy requirements in their modeling. This results in a higher difference, mainly through the balance sheet channel. The authors suggest that monetary authorities could use this effect to smooth the business cycle generated by the potential rise in agency costs.

3. The Financial Crisis

The recent financial crisis presents monumental challenges to regulatory design. This issue is discussed by Garry Schinasi who proposes a new regulatory framework that can generate the appropriate incentives and establish clear rules. The author holds that the current framework is flawed in the excessive confidence in private risk management and market discipline. Similarly, Claudio Borio and Mathias Drehmann discuss the difficulties of establishing an adequate regulatory framework when the authority observes only incomplete or lagged financial fragility indicators.

The papers by Charles Goodhart, Dimitrios Tsomocos, and Alexandros Vardoulakis and by Michael Bordo present proposals for understanding the current financial crisis. The former paper uses a model of heterogeneous agents for banks and households. The results show that monetary policy may help tame the effects of financial market illiquidity (which is consistent with the results found by Kiyotaki and Moore, 1997) and that bank provisions could have a role in times of scarce liquidity. Michael Bordo critically reviews the main milestones of the financial crisis. In his conference paper, he argues that the pressure on business cycles, generated by financial bubbles, originates in loan allocation. His conclusions stress that the lessons of the current financial crisis will strengthen the U.S. banking market and beef up the conviction that the coordination and efficacy of regulators are crucial elements in these extreme scenarios.

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A Historical Perspective on the Crisis of 2007–08

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The current international financial crisis is part of a perennial pattern. Today's events echo earlier big international financial crises that were triggered by events in the U.S. financial system. Examples include the crises of 1857, 1893, 1907, and 1929–33. This crisis has many similarities to those of the past, but also some important modern twists.

The crisis started in the United States with the collapse of the subprime mortgage market in early 2007 and the end of a major housing boom. It occurred following two years of rising policy interest rates. Its causes include major changes in regulation, lax oversight, relaxation of normal standards of prudent lending, and a prolonged period of abnormally low interest rates. Defaults on mortgages spread to investment banks and commercial banks in the United States and across the world via an elaborate network of derivatives. It has recently spilled over into the real economy through a virulent credit crunch and collapsing equities market, which will likely produce a significant recession. The U.S. Federal Reserve and other central banks have responded in a classical way by flooding the financial markets with liquidity, and the fiscal authorities are also dealing with the decline in solvency in the banking system following the template of earlier bailouts like the Reconstruction Finance Corporation (RFC) in the 1930s, Sweden in 1992, and Japan in the late 1990s.

This paper provides a historical perspective on the current crisis, contrasts the old with the modern, and offers some lessons for policy. Section 1 describes the crisis in a bit more detail. Section 2 provides some descriptive empirical evidence putting the crisis in long-run perspective. Section 3 presents some historical parallels

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and modern twists of the crisis. Section 4 discusses some of the issues in historical perspective for the emerging market economies. Finally, section 5 concludes with a discussion of the policy issues.

1. The Crisis

The crisis occurred following two years of rising policy interest rates. Its causes include major changes in regulation, lax regulatory oversight, a relaxation of normal standards of prudent lending, and a period of abnormally low interest rates. The default on a significant fraction of subprime mortgages produced spillover effects around the world via the securitized mortgage derivatives into which these mortgages were bundled, to the balance sheets of investment banks, hedge funds, and conduits (which are bank-owned but off the banks' balance sheets), which intermediate between mortgage-backed and other asset-backed commercial paper and long-term securities. The uncertainty about the value of the securities collateralized by these mortgages spread uncertainty about the soundness of loans for leveraged buyouts. All of this led to the freezing of the interbank lending market in August 2007 and substantial liquidity injections subsequently by the U.S. Federal Reserve and other central banks.

Since then, the Fed both extended and expanded its discount window facilities and cut the funds rate by 300 basis points. The crisis worsened in March 2008 with the rescue of the Bear Stearns investment bank by J.P. Morgan, backstopped by funds from the Federal Reserve. The rescue was justified on the grounds that Bear Stearns's exposure to counterparties was so extensive that a worse crisis would follow if it were not bailed out. The March crisis also led to the creation of a number of new discount window facilities which gave investment banks access to liquidity and which broadened the collateral acceptable for discounting. The next major event was a Fed-Treasury bailout and partial nationalization of the insolvent government-sponsored enterprises (GSEs), Fannie Mae and Freddie Mac, in July on the grounds that they were crucial to the functioning of the mortgage market.

Events took a turn for the worse in September, when the Treasury and the Fed allowed the investment bank Lehman Brothers to fail in an attempt to prevent moral hazard by to discouraging the belief that all insolvent institutions would be saved. It was argued that Lehman was both in worse shape and less exposed to counterparty

risk than Bear Stearns. The next day the authorities bailed out and nationalized the insurance giant AIG, fearing the systemic consequences for collateralized default swaps (insurance contracts on securities) if it were allowed to fail. The fallout from the Lehman bankruptcy then turned the liquidity crisis into a full-fledged global credit crunch and stock market crash (as described in Kindleberger, 1978) as interbank lending effectively seized up on the fear that no banks were safe.

In the ensuing atmosphere of panic, along with Fed liquidity assistance to the commercial paper market and the extension of the safety net to money market mutual funds, the U.S. Treasury sponsored its Troubled Asset Relief Plan (TARP) whereby $700 billion could be devoted to the purchase of heavily discounted mortgage-backed and other securities to remove them from the banks' balance sheets and hopefully restore bank lending. The bill was initially rejected by the Congress, but it was passed a week later after the Senate added on many politically popular and expensive items.

In early October, the crisis spread to Europe and to the emerging countries as the global interbank market ceased functioning. The U.K. authorities responded by pumping equity into British banks, guaranteeing all interbank deposits, and providing massive liquidity. The E.U. countries responded in kind. On 13 October, the U.S. Treasury followed suit with a plan to inject $250 billion into the U.S. banks to provide insurance of senior interbank debt and unlimited deposit insurance coverage for non-interest-bearing deposits. Time will tell whether these plans, which are similar to earlier, mainly successful, rescue packages like the RFC in the United States in the 1930s and the Swedish and Japanese rescues in the 1990s, may solve the solvency crisis.

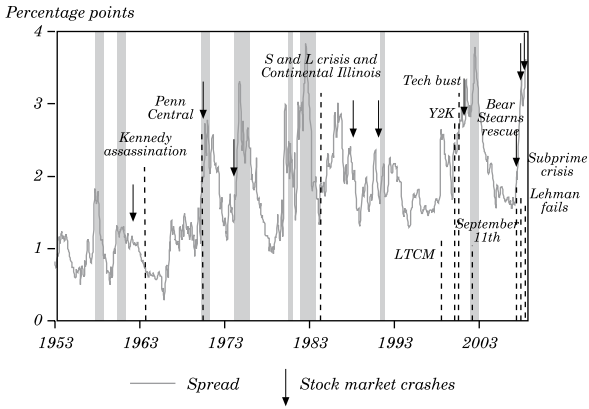
2. Some Descriptive Historical Evidence

Today's turmoil must be viewed in historical perspective. Figure 1 provides some background evidence for the United States over the past century. Panel A, from 1953 to September 2008, shows the monthly spreads between the Baa corporate bond rate and the ten-year Treasury constant maturity (TCM) bond rate. The spread represents a measure of the financial market's assessment of credit risk, as well as a measure of financial instability reflecting asymmetric information (Mishkin, 1991). Figure 2 takes a longer view

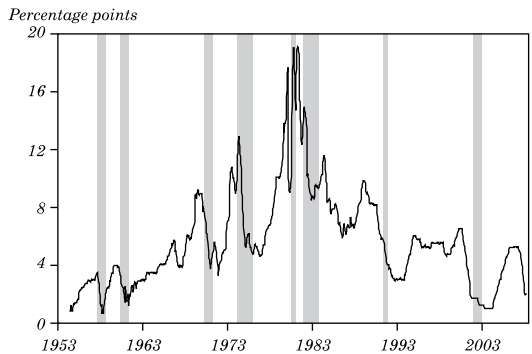
and shows the Baa corporate bond rate and the ten-year composite Treasury bond rate from 1921 to September 2008. Also displayed in both figures are National Bureau of Economic Research (NBER) recession dates and major financial market events, including stock market crashes, financial crises, and some major political events that affected financial markets. Panel B of figures 1 and 2 show policy interest rates—namely, the Federal funds rate since 1953 and the discount rate for the twentieth century, respectively.

Figure 1. The Federal Funds Rate and the Spread between Baa Corporate and Ten-Year TCM Bonds

A. The Baa–TCM spread

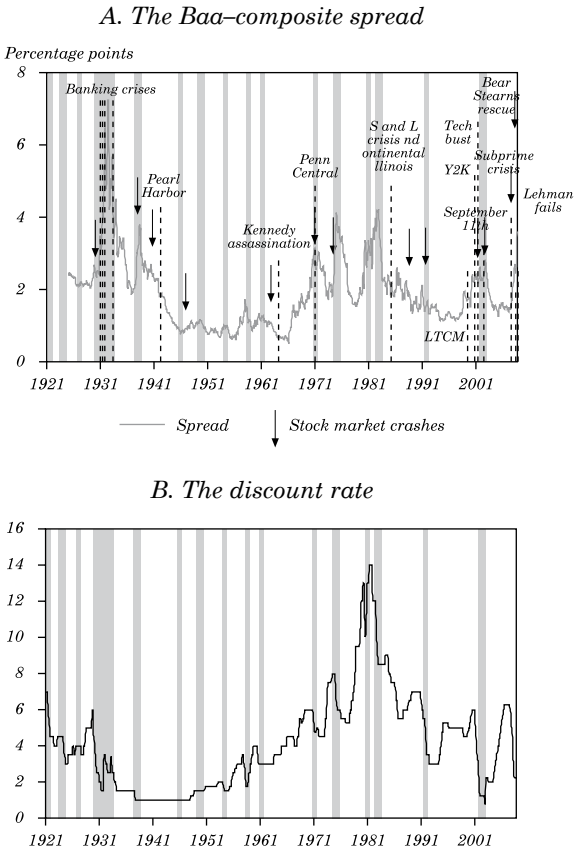


B. The Federal funds rate



Sources: Federal Reserve Board and NBER.

Figure 2. The Discount Rate and the Spread between Baa Corporate and Ten-Year Composite Treasury Bonds



Sources: Federal Reserve Board and NBER.

As can be seen, the peaks in the credit cycle (proxied by the spreads) are often lined up with the upper turning points in the NBER reference cycles. Many of the events, especially the stock market crashes and the banking crises of the 1930s, occur close to the peaks. Moreover, panel B often shows the policy rate peaking very close to or before the peaks of the credit cycle. Its movements roughly reflect the tightening of policy before the bust and loosening in reaction to the oncoming recession afterward. In the recent crisis, by September 2008 the Baa ten-year TCM spread reached levels

comparable to that reached in the last recession in 2001–02 and above that of the credit crunch of 1990–91. The Baa ten-year composite spread was just below the spreads in the early 1980s recession after the Volcker shock and President Carter's credit restraint program. All of these events were associated with significant recessions.

3. Historical Parallels and Modern Twists

Many of the financial institutions and instruments caught up in the crisis are part of the centuries-old phenomenon of financial innovation. The new instruments, which are often devised to avoid regulation, are then put to the test when an economy experiences financial stress such as we have been recently encountering. The rise and fall of financial institutions and instruments occurs as part of a long-standing pattern of booms and busts in the markets for equities, land, commodities, foreign exchange, and other assets. The cycle is financed by credit. Lending booms and busts and the credit cycle are also intimately connected to the business cycle.

A well-known tradition in monetary economics, which goes back to the nineteenth century and in the twentieth century was fostered by Mitchell (1913), Fisher (1933), Minsky (1977), Kindleberger (1978), and others, tells the tale of a business cycle upswing driven by what Fisher called a displacement (that is, an exogenous event that provides new profitable opportunities for investment) leading to an investment boom financed by bank money (and accommodative monetary policy) and by new credit instruments (financial innovation). The boom leads to a state of euphoria in which investors have difficulty distinguishing sound from unsound prospects and in which fraud can be rampant. It can also lead to a bubble characterized by asset prices rising independently of their fundamentals. The boom inevitably leads to a state of overindebtedness, when agents have insufficient cash flow to service their liabilities. In such a situation, a crisis can be triggered by errors in judgment by debtors and creditors in an environment changing from monetary ease to monetary tightening. The crisis can lead to fire sales of assets, declining net worths, bankruptcies, bank failures, and an ensuing recession.

A key dynamic in the crisis is information asymmetry, manifest in the spread between risky and safe securities (Mishkin, 1997). Information asymmetry promotes adverse selection and moral hazard, which are ignored in the boom and come into play with a vengeance in the bust.

Banks played a key role in the traditional story because bank credit largely financed the boom, and the bust was often accompanied by bank failures and banking panics—events which eventually made the downturn worse. This led to the traditional case for the monetary authority to act as a lender of last resort and provide liquidity at penalty rates to the money market and discount window lending to solvent but illiquid banks.

Countercyclical monetary policy is also an integral part of the boom-bust credit cycle. Bordo and Wheelock (2007, 2009) use data for the United States and nine other countries for the past century to show that stock market booms occur in environments of low inflation, rising real GDP growth, and low policy real interest rates. Before World War II, central banks operated under the gold convertibility constraint, so they inevitably tightened their policy rates as the boom progressed and inflationary pressure grew, thus helping to trigger the ensuing crash. The story is similar for housing booms and busts, but they follow a different cycle because of long gestation lags in construction and in the adjustment of prices to a collapse in demand (Leamer, 2007).

Stock market crashes can be serious events leading to a decline in wealth and consumption and a scramble for liquidity, which, in turn, contributes to incipient banking crises. Housing busts also have serious consequences for the banking system, via defaults on mortgages, and for the real economy, via the effect of declining wealth on consumption expenditure, the collapse of residential investment, and a financial accelerator effect as net worths decline. The recent housing boom in the United States was largely triggered by a long period of abnormally low interest rates, attributed to loose monetary policy in 2001–04 in reaction to earlier financial turbulence and fear of deflation and to a global savings glut (Bernanke, 2007). The bust was likely induced by a rise in rates in reaction to the inevitable inflationary pressure.

3.1 The Nonbank Financial Sector, Financial Innovation, and Financial Crises

The traditional financial crisis story depicts a shock to a major financial or nonfinancial firm, which leads to a banking panic as depositors attempt to convert their deposits into currency. Since the advent of deposit insurance, the source of the pressure has come from the asset side, rather than the liability side, of a bank's balance sheet.

One example is the Penn Central episode in 1970, when the collapse of the railroad led to a panic in the commercial paper market and triggered concern by the Fed that it would spill over into the banking system. The New York Federal Reserve responded by opening the discount window to the money center banks to freely discount nonfinancial firms based on the collateral of sound commercial paper. Other examples include the Latin American debt default of 1982, when many money center banks became close to insolvent until a massive rescue was orchestrated between the Fed and the IMF, and the collapse of the Long-Term Capital Management (LTCM) hedge fund in 1998, which also was perceived to be a threat to the banking system. LTCM was rescued when the New York Federal Reserve orchestrated a lifeboat operation by the New York banks. Historically, in 1763 a crisis in the market for bills of exchange spread from Amsterdam to Hamburg and, like LTCM, led to the failure of the principal player and many others (Schnabel and Shin, 2001). In each of these cases, the crisis broke in the nonbank financial sector and then spilled over or threatened to spill over into the banks, who were the ultimate creditors.

Many of the financial crises of the past involved financial innovation that increased leverage. The 1763 crisis was centered on the market for bills of exchange, Penn Central on the newly revived (in the 1960s) commercial paper market, the savings and loan crisis on the junk bond market, and LTCM on derivatives and hedge funds.

3.2 Modern Twists

Although there are many historical parallels to the current crisis, there are several unique differences. In the most recent episode, the financial innovation derived from the securitization of subprime mortgages and other loans has shifted risk away from the originating banks into mortgage-backed and other asset-backed securities, which bundle the risk of less stellar borrowers with more creditworthy ones and which were certified by the credit rating agencies as prime. These were absorbed by hedge funds in the United States and abroad and in the asset-backed commercial paper of the commercial and investment banks. As Rajan (2005) presciently argued, shifting the risk away from banks, which used to have the incentives to monitor their borrowers, to hedge funds and other institutions, which do not, increased overall systemic

risk by raising the risk of a much more widespread meltdown in the event of a tail event, as we have recently witnessed.

A key modern twist was the growth of the nonbank financial sector (a shadow banking system) that was not regulated by the central bank or covered by the financial safety net. According to Eichengreen (2008), its rapid growth was a consequence of the repeal in 1999 of the Depression era Glass-Steagall Act, which separated commercial from investment banking. These institutions held much lower capital ratios than traditional commercial banks and hence were considerably more prone to risk. When the crisis hit, they were forced to engage in major deleveraging involving the fire sale of assets into a falling market, which in turn lowered the value of their assets and those of other financial firms. A similar negative feedback loop occurred during the Great Depression (Friedman and Schwartz, 1963).

4. Prospects for the Emerging Markets

Financial crises have always had an international dimension, as Morgenstern (1959), Kindleberger (1978), and Bordo (1986) have shown. Contagion spreads quickly through asset markets, through international banking, and through the monetary standard. Stock market crashes and banking panics have often occurred in many countries within a few months of the original shock. A classic example is the Baring crisis of 1890, which started in Argentina and affected the rest of Latin America and other emerging countries of the time. It was triggered by central bank tightening in England, France, and Germany. This led to a series of sudden stops and current account reversals (Bordo, 2006) in the emerging countries and a number of banking crises and debt defaults. These events were echoed in the late 1990s (see Calvo and Talvi, 2005).

The current crisis was initially contained to the advanced countries, among which contagion was spread by the holding of opaque subprime mortgage derivatives in diverse banks in Europe and elsewhere and by the seizing up of the asset-backed (mortgage-backed) commercial paper market. Pressure then spilled over to the emerging markets, especially those who were highly indebted to the advanced countries, with high current account deficits and significant exposure to the advanced countries' boom, as in the case of Iceland, Hungary, and Ukraine (IMF, 2008, chap. 1). The IMF and the European Central Bank initiated rescues. Many of the Asian

countries (and some Latin American economies) have avoided the worst of the crisis, likely because of the precautionary measures many took in reaction to their meltdowns in the Asian crisis of 1997 (for example, the build up of large foreign exchange reserves and a reduction in their exposure to foreign borrowing). As the credit crunch continues and the recession in the United States and Europe plays out, the emerging economies that are exposed to foreign capital have been more strongly affected, as have countries that rely on exports to the United States and Europe.

5. Policy Lessons

The crisis has implications for monetary policy on the key issues of liquidity, solvency, and the stability of the real economy. With respect to liquidity, the central banks reacted quickly in the Bagehot (1873) manner to deal with the freezing of the interbank markets in August 2007. The European Central Bank flooded the European money market with liquidity, as did the Fed in the U.S. market when it lowered the discount rate by 50 basis points. This suggests they heeded the first part of Bagehot's lesson to lend freely, but not quite the second part of lending at a penalty rate. The Bank of England followed a strict interpretation of Bagehot until mid-2007, by keeping its discount window open to all comers but at a penalty rate. The subsequent run on Northern Rock on 14 September led to a large infusion of central bank liquidity and the announcement of a temporary complete guarantee of all U.K. bank deposits. The run on Northern Rock very likely reflects not the failure of the Bank's lender-of-last-resort policy, but inadequacies in the United Kingdom's provision of deposit insurance, the ill-thought-out separation of financial supervision and regulation from the central bank and political pressure (Milne and Wood, 2008).

The pressure on the interbank market and liquidity in general increased during the winter of 2007–08. In March, with the Bear Stearns crisis, the Fed developed a series of new programs for access to the discount window, including the Term Auction Facility (TAF), the Term Security Lending Facility (TSLF), and the Primary Dealer Credit Facility (PDCF). Since March, the Fed has also expanded its liquidity provision to the commercial paper market.

These facilities reflected a change in the Fed's tactics. The change involved the provision of credit directly to the financial firms that the Fed deemed most in need of liquidity, as opposed to delivering

liquidity directly to the market through open market purchases of Treasury securities and then letting the market distribute liquidity to individual firms. The choice of targeted lending instead of imperial liquidity provision by the market exposed the Fed to the temptation to politicize its selection of credit recipients. This raises the question of why this complicated method of providing liquidity has been introduced when the uncomplicated system of open market operations is available. A second question is why the Fed has reduced its holdings of government securities. This will make it impossible for the Fed to tighten monetary policy when it finally decides to combat a rise in the inflation rate, since the only way to tighten is to sell government securities. The mortgage-backed securities now on the Fed's balance sheet are not marketable.

With respect to solvency, the Fed and the other U.S. monetary authorities have engaged in a series of bailouts of incipient insolvent firms deemed too systemically connected to fail. These include Bear Stearns in March 2008, the GSEs in July, and AIG in September. Lehman Brothers was allowed to fail in September 2008 on the grounds that it was basically insolvent and not as systemically important as the others. One wonders whether the severe crisis in September–October 2008 could have been avoided if Bear Stearns had been allowed to fail. Had Bear Stearns simply been closed and liquidated, it is unlikely that more demand for Fed credit would have come forward. The fact that general creditors and derivative counterparties of Bear Stearns were fully protected by the merger of the firm with J.P. Morgan Chase had greater spillover effects on the financial services industry than would have been the case had the Fed appointed a receiver and frozen old accounts and payments as of the date of the appointment. Fewer public funds would have been subjected to risk. When Drexel Burnham Lambert was shut down in 1990, there were no spillover effects.

Furthermore assume, as the Fed argued at the time, that there would have been a crisis in March like the one that followed Lehman's failure in September. Would it have been as bad as the latter event? The moral hazard implications of bailing out Bear Stearns most probably led the remaining investment banks and other market players to follow riskier strategies than otherwise on the assumption that they also would be bailed out. This surely made the financial system more fragile than otherwise. Consequently, when the monetary authorities decided to let Lehman fail, the shock that ensued and the damage to confidence was much worse.

The September 2008 crisis revealed that the deepest problem facing the financial system is solvency. The problem stems from the difficulty of pricing securities backed by a pool of assets, whether mortgage loans, student loans, commercial paper issues, or credit card receivables. Pricing securities based on a pool of assets is difficult because the quality of individual components of the pool varies, and an accurate price of the security cannot be determined unless each component is individually examined and evaluated. As a result, the credit market—confronted by financial firms whose portfolios are filled with securities of uncertain value, derivatives that are so complex the art of pricing them has not been mastered—is plagued by the inability to determine which firms are solvent and which are not. Lenders are unwilling to extend loans when they cannot be sure that a borrower is creditworthy. This serious shortcoming of the securitization process is responsible for the paralysis of the credit market.

The Fed was slow to recognize the solvency problem. It emphasized providing liquidity to the market when the problem was the market's uncertainty about the solvency of individual or sectoral financial firms. No financial market can function normally when basic information about the solvency of market participants is lacking. The securities that are the product of securitization are the root of the turmoil in financial markets, which began long before the housing market burst.

The Treasury's plan of 13 October 2008, based on the U.K. plan to inject capital into the banking system, seems likely to help solve this problem. However, it is not clear whether funds will be injected into insolvent banks or into solvent banks that are temporarily short of capital. If funds go to insolvent banks, this can only prolong the credit crunch.

There is ample historical precedent for the Treasury plan, including the RFC established by the Hoover administration in 1932. Under Roosevelt, it injected $1.3 billion to 6,000 banks, which is equivalent to $200 billion in equity today.[1] The RFC's efforts were hampered in 1932 by the publication of the list of banks raising capital. This led to runs on these banks and unwillingness by others to participate. The current Treasury plan also has precedent in the Swedish bank bailout of 1992 and Japan's long-delayed bailout in the late 1990s.

1. Richard Sylla, remarks on the NewsHour with Jim Lehrer, PBS, 15 October 2008.

With respect to the real economy, the Fed, with its dual mandate of price stability and high growth (full employment), did follow the correct policy in cutting the Funds rate as vigorously as it did. Considerable empirical and historical evidence suggests that credit crunches exacerbate recessions (see figures 1 and 2 and IMF, 2008, chap. 4). Given the Fed's dual mandate, the risk of recession following the credit crunch seems to be a reasonable rationale for a temporary easing of monetary policy. Once recovery is in sight and once inflationary expectations pick up, it behooves the Fed to return to its (implicit) inflation target.

Another lesson concerns whether the Fed should continue to follow its reactive policy to asset booms or move to a preemptive policy. The traditional view of monetary policy argues that central banks should act reactively and deal with the consequences for the financial system of an asset price boom after it has burst (Bernanke and Gertler, 2001). An alternative view argues that if an asset bubble (such as housing) is on the horizon, then the Fed should act preemptively to defuse it (Cecchetti and others, 2000). Bordo and Jeanne (2002) consider a circumstance in which the use of preemptive policy against the occurrence of a low probability event that could have catastrophic consequences, such as a national housing bust, can be welfare improving. Perhaps the recent events will convince the Fed to change its stance.

An additional lesson speculates on the genesis of the crisis. The recent financial crisis likely could have been avoided if the Fed had not provided as much liquidity as it did from 2001 to 2004. When no financial crisis occurred after Y2K, it promptly withdrew the massive infusion of liquidity it had provided. By contrast, when it later foresaw a series of shocks to the economy that might lead to financial crisis, such as the dot-com bust of 2001 and the 9/11 terrorist attack, it injected liquidity and then allowed the additional funds to remain in the money market when no financial crisis occurred. It also overreacted to the threat of deflation in 2003–04, which may have been of the good (productivity-driven) variety rather than the bad (recessionary) variety (Bordo and Filardo, 2005). If, following these events, the market had not been infused with so much liquidity for so long, then interest rates would not have been as low in recent years as they were and the housing boom may not have expanded as much as it did. Taylor (2007) thus suggests that interest rates in this period were, on average, considerably lower than would be the case based on his famous rule.

5.1 Some Less Gloomy Lessons from the Crisis

Finally, there are some less gloomy lessons from the crisis. First is the compressed consolidation of the U.S. banking industry. Since the 1990s, the U.S. banking system has been slowly consolidating to take advantage of the removal of barriers to interstate banking and branch banking. Canada and most European countries went through this consolidation by mergers and acquisition in the late nineteenth and early twentieth centuries. Evidence suggests that the U.S. banking system historically was both less stable and less efficient than its Canadian counterpart (Bordo, Redish, and Rockoff, 1996). The recent crisis has forced mergers and exits, thereby facilitating the move to a banking system closer to those of the other advanced countries, characterized by a few very large banks. Many smaller banks will survive, however, because of the legacy of community banking with significant local social capital.

Second, the crisis is resolving issues raised by the Glass-Steagall act of 1933, which separated commercial from investment banking. Since the act was repealed in 1999, the more lightly regulated investment banks, with their advantage of lower capital requirements, competed successfully with the commercial banks, inducing the latter to increase leverage and move liabilities off their balance sheets. The resultant increase in risk contributed to the crisis. The demise of Bear Stearns and Lehman Brothers has forced the other investment banks to merge with major commercial banks, to come under the umbrella of the Fed and Federal Deposit Insurance Corporation safety nets. The creation of such universal banks has returned the United States to the system it had before Glass-Steagall and moves it closer to the banking systems in some European countries. Universal banks have a long history of stability and efficiency (Fohlin, 2007).

Third, the extension of the lender-of-last-resort function to include most types of collateral and most financial institutions seems to be following some of Bagehot's (1873) strictures on what the central bank should do in a panic. In describing what a Bank of England's director said about its actions in the crisis of 1825, Bagehot states that "we lent it by every possible means and in modes we never adopted before; we took in stock on security, we purchased Exchequer bills, we not only discounted outright, but we made advances on the deposits of bills of exchange to an immense amount, in short by every means consistent with the safety of the Bank, and we were not on some occasions over-nice. Seeing

the dreadful state in which the public were, we rendered every assistance in our power" (p. 52).

Finally, the monetary authorities in the United States and Europe responded quickly to resolve both the liquidity and solvency aspects of the crisis. This contrasts with the Great Depression, when the Fed did virtually nothing and it was up to Franklin D. Roosevelt and the Treasury to jump start the economy by devaluing the dollar in 1933 and purchasing gold thereafter. It also contrasts with the slow response of the Japanese authorities following the collapse of Japan's stock market and real estate bubbles.

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Defining Financial Stability and Establishing a Framework to Safeguard It

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The ongoing global financial crisis has been a rude awakening that the current framework for safeguarding financial stability is neither reliable nor effective. The threats to global economic stability caused by the dysfunction of credit and money markets and the weakening of the global banking system also make clear that safeguarding the stability of the financial system is as important a policy objective as maintaining monetary stability if economic growth and stability are to be achieved and sustained.

Despite the global financial industry's importance measured in terms of value added to global production and employment, global finance is not an end in and of itself. It is, instead, a means to enhancing and facilitating the efficiency of economic processes such as resource allocation, risk allocation and pricing, wealth accumulation, and ultimately economic growth and prosperity.

The massive and destructive deleveraging still underway signals that the global financial industry has been missing this point for quite some time—as if finance existed for the benefit of highly paid financiers and outsized rates of return. However, much of the virulence of this crisis could not have occurred without the policy shortcomings and mistakes that inadvertently either encouraged or acquiesced to excessive risk taking and the accumulation of imbalances. Playing key roles in this regard were misaligned private incentives, ineffective regulations and business practices

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(or rules of the game), and inadequate official oversight of financial institutions and markets, not to mention excessively expansionary global monetary and macroeconomic policies.

The financial system policy framework in place prior to the crisis—which has already been transformed significantly in the United States and Europe—failed dramatically. This framework was a patchwork of rules of the game and regulatory and supervisory principles and institutions that emerged in the aftermath of the Great Depression and which has since evolved in response to repeated, but individually unique, experiences of economic cycles of growth and recessions, financial cycles of boom and bust, and dramatic and at times system-transforming financial innovation. In effect, the policy apparatus for safeguarding financial stability did not keep pace with financial innovation, modernization, and globalization and failed to prevent financial imbalances from arising, accumulating, and compounding, to the point of a global systemic financial crisis and quite possibly the worst global economic crisis since the 1930s.

The resulting framework relied too heavily (and naively) on private risk management and market discipline to safeguard financial stability and not enough on appropriate incentives, effective rules of the game, and well designed and rigorously implemented official oversight. The balance of emphasis in policy will likely now swing in the direction of realigning private and public incentives, redesigning new rules of the game appropriate for a modern global financial system, and significantly enhancing the reliance on official oversight through improved supervision of institutions and surveillance of markets. These efforts should also include reforms to enhance financial reporting, disclosure, and market transparency in an effort to improve the effectiveness of market discipline in preventing the build up of catastrophic financial imbalances.

A prerequisite for more effective official oversight is the development and implementation of a more effective framework for assessing the financial system's ability to perform its key economic functions.[1] However, the ultimate objective of promoting efficient finance and of safeguarding financial stability once it is achieved

1. The key functions include matching the needs of savers and investors; providing transactions and payments services; risk pricing, spreading, sharing, and management; and the production, processing, and monitoring of information.

is sustained economic growth, stability, and prosperity. From this perspective, no policy framework can effectively safeguard financial stability if it does not place these core objectives front and center, including in the very definition of financial stability.

With this as background, the purpose of this paper is twofold: first, to establish a definition of financial stability and create a framework for policy analysis that is more closely aligned with economic processes and efficiency; and, second, to examine the implications and challenges for assessing systemic risk and safeguarding financial system stability. The definition links the effectiveness of finance and the financial system to its ability to facilitate the efficiency of economic processes such as wealth accumulation, economic growth, and economic efficiency more generally, as well as risk pricing and management. This means that assessing the stability of the financial system would become a vital step in evaluating the stability of the economy in general and the appropriateness of microeconomic and macroeconomic policies. This perhaps makes assessing financial stability even more challenging than assessing the potential for instability, but this way of framing the intermediate objective of safeguarding financial stability at least offers the possibility of designing policies that proactively promote economic efficiency and health. This more positive and proactive disposition could reap benefits in terms of warding off the accumulation of the kind of financial imbalances that could threaten financial stability.

The paper is organized as follows. The next section of the paper briefly discusses the existing framework of prevention and resolution of financial instability. This framework relied heavily on lines of defense against financial instability, almost as if finance were some kind of disease. All of the existing lines of defense failed to prevent the subprime crisis from occurring and, importantly, from spreading to all other international financial centers. The paper then motivates a definition of financial stability and relates it to economic processes and economic efficiency. This section argues that the concepts of financial efficiency and economic stability cannot be separated as clearly as they are in theoretical micro- and macroeconomic analysis, in part because finance is not an end, but a means to promoting economic efficiency, growth, and stability. If finance is ineffective and prone to repeated systemic booms and busts, it is unlikely to promote intertemporal economic efficiency and may even promote intertemporal inefficiency, as seems to be the

case in the ongoing global crisis. Finally, the paper discusses some of the more important challenges in assessing financial stability in an effort to safeguard the financial system from potential financial imbalances. An implication of the analysis is that intertemporal efficient wealth accumulation and growth can only be safeguarded with a financial stability framework that incorporates and integrates important elements of economics and finance, at both the macro- and microeconomic levels.

1. Existing Policy Framework

The existing policy framework for safeguarding financial stability has evolved through time based, in part, on the realizations that finance is subject to market imperfections and that it is a public good. This framework has been portrayed in officialdom as a series of lines of defense against financial imbalances that could arise, and have arisen often enough, from underlying structural market imperfections and unexpected shocks. The lines of defense have been designed to prevent imbalances from becoming systemic and to resolve systemic difficulties should one or more of the defenses be breached. This section briefly summarizes the existing framework within the context of cross-border finance, although the framework presented is also a reasonable characterization of existing national and regional frameworks in advanced countries and the major international financial centers.

1.1 Policy Issues and Concerns

At the global level, the channels through which financial instability can be transmitted from one country to another can usefully be classified into three broad categories: institutions, markets, and infrastructures. This triad—together with legal and monetary arrangements, business practices, and codes of conduct—provides a reasonable definition of what is normally meant by the term financial system, which is discussed more fully later. Cross-border linkages of components of this triad can be seen as constituting the main channels through which problems in one national financial system get transmitted to another. In addition to these financial channels, the global economy is probably the most basic and prevalent cross-border transmitter of economic or financial weaknesses, but this is

the purview of macroeconomists and macroeconomic policymakers and not this paper.

To provide context, table 1 summarizes some public policy issues and concerns around which the existing policy framework has evolved. Roughly speaking, the issues involve one or more market imperfections (or market failures). Three broad global policy issues (specified in the three rows of table 1) arise to varying degrees from three potential channels of systemic concern (the three columns of the table). The policy issues are protecting investors and markets, dealing with safety net issues and moral hazard, and assessing and mitigating cross-border and systemic risk. The three channels are cross-border banks, foreign exchange and other global markets, and unregulated entities, such as hedge funds, structured investment vehicles (SIVs), and other special purpose vehicles.

All three issues are very important for banks generally and cross-border banks in particular. They are all also important for global markets. Investor protection and safety net issues are widely seen as not being relevant for unregulated entities, while the most recent crisis clearly indicates that unregulated entities can pose systemic risk.

Table 1. Public Policy Issues and Concerns

	Policy domain of cross-border systemic concern		
Policy issues and concerns	*Cross-border institutions*	*Global (FX) markets*	*Unregulated activities*
Investor protection and market integrity?	Investor protection	Market integrity	No; possibly for retail investors (of funds of funds)
Moral hazard from safety net?	Yes; also home/host burden-sharing issues	Possibly from G-3 central bank liquidity	No
Cross-border and systemic risks?	Maybe, depending on size, complexity, etc.	Yes, via over-the-counter markets and infrastructure linkages	Yes, via opacity, complexity, and with institutions and markets

Source: Author's assessment.

1.2 Policy Framework

Taking this classification as given, table 2 presents how these risks and public policy concerns are addressed through financial policies. It tries to answer the question: To what extent are the tools of financial policies used to address these concerns?

Table 2. Oversight Regimes

	Policy domain of cross-border systemic concern		
Lines of defense	*Cross-border institutions*	*Global (FX) markets*	*Unregulated activities*
Market discipline	Partially	Primarily	Exclusively
Market and banking regulation	National with cooperation	Not really; over-the-counter transactions	No
Prudential supervision	National and home/host issues	n.a.	No
Market surveillance	Indirect, as participant	Direct, national and international	Indirect, as participant

Source: Author's assessment.

As indicated in the first column of table 2, large cross-border banking groups, including the large internationally active banks, are probably the most closely regulated and supervised organizations on the planet, and for good reasons. These institutions pose financial risks for depositors, investors, markets, and even unrelated financial stakeholders because of their size, scope, complexity, and risk taking. Some of them are intermediaries, investors, brokers, dealers, insurers, reinsurers, or infrastructure owners and participants—and a single complex institution can sometimes play several of these roles. Cross-border institutions are systemically important: all of them nationally, many of them regionally, and about twenty or so of them globally. Protection, safety net, and systemic risks are key pubic policy challenges. Finally, oversight occurs at the national level, through both market discipline and official involvement, and at the international level, through committees and groups. As a result, banks, generally, and cross-border and global banks are probably the most closely watched financial institutions in the world.

At the other extreme of regulation and supervision are unregulated entities, shown in the right-most column of table 2. They are neither regulated nor supervised. Many of the financial instruments that these unregulated entities strategically and tactically use, such as over-the-counter (OTC) derivatives, are not subject to securities regulation, and the markets in which they transact are by and large the least regulated and supervised. This is part of the investment strategy, and it defines the scope of profit making. Unregulated entities (including hedge funds and certain kinds of SIVs) are forbidden in some national jurisdictions. In jurisdictions where they are partially regulated, this is tantamount to being forbidden, given the global nature and fungibility of the hedge-fund business model. A key characteristic of unregulated entities is that while their market activities are subject to market surveillance just like other institutions, this does not make transparent who is doing what, how they are doing it, and with whom they are doing it. Investor protection is not an issue for most individual unregulated entities, as they restrict their investor base to institutions (such as pension funds, insurance companies, and hedge funds) and wealthy individuals willing to invest in relatively high minimum amounts. It is, however, increasingly an issue for hedge funds, with the advent of funds-of-hedge-funds that allow minimum investments of relatively small amounts less than $100,000 or even less than $50,000 in hedge funds. Finally, concerns that hedge funds may represent a potential systemic risk have increased since the Asian and Long-Term Capital Management (LTCM) crises, particularly considering their tremendous growth over the past several years; I return to this theme below.

Global markets fall in between being and not being regulated and supervised. Global markets include the foreign exchange markets and their associated derivatives markets (for both exchange-traded and over-the-counter derivatives) and the fixed-income markets and their associated derivatives markets. Dollar, euro, and yen government bonds are traded more or less in a continuous global market, and the associated derivatives activities are also global.

Global markets are only indirectly regulated. They are subject to surveillance through private international networks and business-cooperation agreements, through information sharing by central banks and supervisory and regulatory authorities, and through official channels, committees, and working groups. Parts of these markets are linked to national clearance, settlement, and

payments infrastructures, so they are also subject to surveillance through these channels. The risks they potentially pose are less of a concern to the extent that the major players in them—namely, the large internationally active banks—are supervised and market disciplined by financial stakeholders. If there is poor oversight of the major institutions, then these global markets are subject to considerable risks, including a greater likelihood of systemic risk. One obvious example would be the global over-the-counter derivatives markets, which are unregulated and have little oversight except through the regulation and supervision of the institutions that engage in the bulk of these markets' activities. Both investor protection and systemic risk are challenging public policy issues for these markets.

Regarding infrastructure, large internationally active institutions typically are major participants in domestic and international clearance, settlement, and payments infrastructures—both public and private—as well as the major trading exchanges. Many of them co-own parts of the national and international infrastructures and have a natural interest in their performance and viability. Incentives are, to some extent, aligned to achieve both private and collective net benefits. Increasingly, however, internationally active banks have been more heavily involved in OTC transactions, which do not pass through these infrastructures. This poses challenges in terms of systemic risk, many of which have surfaced dramatically in the ongoing global financial crisis.

1.3 Lines of Defense against Systemic Risks and Events

As the rows of table 2 make clear, this framework relies on four lines of defense for preventing problems from occurring and becoming systemic and for dealing with them when they do become systemic (nationally, regionally, and globally). These can be roughly categorized as private risk management; market discipline; official oversight; and crisis management and resolution mechanisms.

—Private risk management includes financial-risk management at business-line levels; enterprise risk management at the firm level; management controls at executive and senior-management levels; corporate governance at the board level; and self-regulation via development and promotion of best business practices.

—Market discipline encompasses sound accounting and valuation procedures for properly recording and valuing financial

transactions and statements; the timely reporting and disclosure to allow investors to assess risks; well-functioning markets for price discovery and resource and risk allocation; and legal infrastructure for the enforcement of financial contracts.

—Key features of public sector oversight include transparent and enforceable legal infrastructure; effective market regulation and surveillance; and effective oversight of financial institutions, in which the banks are the most heavily regulated and supervised, investment banks are subject to SEC regulations, insurance and reinsurance are lightly regulated, other institutional investors are lightly regulated, and some activities are unregulated.

—Finally, crisis management and resolution mechanisms involve deposit insurance protection to prevent bank runs; appropriate liquidity provision by the central bank to keep markets functioning smoothly; lender-of-last-resort operations to prevent market dysfunctioning and to keep illiquid but viable financial institutions from failing; and capital injections (preferably private rather than public) to maintain orderly transitions for institutions that are not viable.

The ongoing global crisis triggered by the U.S. subprime crisis occurred because most, if not all, of these lines of defense failed in significant ways. The implementation of this framework, whose aim is to prevent instability, was not successful in preventing the kind of imbalances that created systemic risk and systemic events. Moreover, the central banks and fiscal authorities, and in many cases the legislators, in the advanced countries had to become innovative in creating new tools and finding the financing to support them to prevent further damage to both financial systems and economies. Even more innovative reforms and policy tools may be required to regain economic and financial stability.

1.4 In the Breach: Characteristics of the Current Global Financial Crisis

Although the crisis was triggered by the U.S. subprime mortgage crisis and by housing market booms and bubbles in Europe, many other factors also contributed to the crisis, including excessive credit expansion and leverage, lax lending standards, and ineffective official oversight of key markets and participant institutions. These factors have been vetted in official analyses and widely discussed in the press, so I do not discuss them extensively here.

The main features of the crisis can be briefly summarized as follows. First, markets for liquidity and their supporting derivatives markets became dysfunctional, reflecting an underlying breakdown of trust in systemically important counterparty relationships among the large global active financial institutions. Credit markets and their surrounding derivatives markets were similarly dysfunctional, which created further pressures in markets for liquidity and thus further increased the intensity of underlying creditworthiness issues. Second, the market displayed a growing perception of the increasing risk of a prolonged and possibly deep U.S. and global economic recession. Third, key central banks in the major international financial centers lost control of monetary and financial conditions, which reduced their ability to exercise their policy instruments to safeguard both monetary and financial stability. Fourth, a number of innovative policy changes were implemented, including the use of existing facilities in new ways (extended terms and access) and the extension of facilities to nonbank financial intermediaries. At the international level, central banks in advanced countries coordinated their actions. Finally, the United States and Europe extended official financial support to both bank and nonbank financial institutions, and the U.S. Treasury spearheaded a legislative initiative to remove toxic assets and recapitalize weak systemically important institutions.

The bottom line is that the existing policy framework, which relies on a balance of market discipline and official oversight, failed to prevent the imbalances from arising. Moreover, the existing mechanisms for resolving problems from becoming systemic proved to be inadequate. In effect, all lines of defense failed to prevent a relatively small financial problem from becoming systemic, in part because other lines of defense failed earlier on to prevent the buildup of overwhelming and unsustainable imbalances in credit markets, including massive, opaque, highly-leveraged, and essentially unregulated financial structures and securities.

Policymakers are continuing to innovate to create new mechanisms to contain systemic risk and restore confidence and both economic and financial stability. Ultimately, they will need to create a new policy framework and a more sustainable financial system architecture (which has already begun in the United States) to restore and safeguard financial stability.

2. Financial Stability as the Objective

An important prerequisite for success in safeguarding financial stability in the future is the development of an intellectual framework that perceives the safeguarding of financial stability as a policy objective on a par with monetary stability, which has been perceived for several decades as a key prerequisite for sustaining durable economic growth and economic stability more generally.[2] An important component of this intellectual framework will no doubt be the enhanced ability to assess whether the financial system is capable of continuing to perform its main financial and economic functions in the presence of sizable unexpected shocks. Designing a framework for making assessments of this kind must, to some extent, be grounded in a practical conception of what is meant by financial stability and the ability to sustain it. To be useful for assessing the potential for systemic risk and events, the definition and framework must link the performance of the financial system to its ability to facilitate continued economic growth and stability. In short, the framework for assessing financial stability must assess the potential impact of financial vulnerabilities on the real economy. The existing frameworks did this prior to the current crises, but they clearly failed to provide early warnings of the impending financial dysfunctioning and its potential impact on the United States and global economies. The time is ripe for brainstorming and fresh thinking.

One reason why policymakers and academics have relied on concepts of financial instability rather than financial stability is that it is difficult to define what is meant by financial stability. First, stability is a difficult concept to define for an evolving, innovating, organic entity such as a financial system, which is constantly transforming itself. Second, it is difficult to define what is meant by equilibrium in finance, in part because equilibrium prices and resource allocations today depend on expectations of future outcomes, while expectations can be highly volatile if not unstable. Third, the essence of a financial transaction is an IOU or a promissory note involving human trust—the very kind of trust that

2. This section is based on material in Schinasi (2006), Fell and Schinasi (2005), and Houben, Kakes, and Schinasi (2004). I am grateful to my coauthors and to the U.K. National Institute Economic Review for granting permission to use all or part of this material.

policymakers were trying to restore in October 2008. This section tries to motivate and examine a definition of financial stability that has the potential for helping us safeguard financial stability.

2.1 Conceptual Challenges

Public policy typically tries to mitigate the impact of efficiency losses associated with market imperfections. In finance, however, each and every loss of efficiency does not necessarily require intervention. The desirability or necessity of some form of collective intervention is much clearer when a market imperfection in finance leads to an inefficiency that poses a significant threat to financial stability, because of the impact on either financial institutions or markets or both.

Unfortunately, the financial system policy literature rarely makes a clear distinction between sources of market imperfections that threaten stability and those that do not. This is because it is difficult to measure the efficiency losses associated with market imperfections in finance and to assess the risks to financial stability associated with market imperfections. These are some of the challenges in the period ahead, for which an analytical framework for financial stability would be useful for policy purposes.

2.2 Financial Stability Challenge

There are many ways to characterize the challenges to achieving and maintaining financial stability. Moreover, the nature of the challenge will depend on the structure and maturity of the economic system. For mature financial systems, the financial stability challenge can be characterized as maintaining the smooth functioning of the financial system and its ability to facilitate and support the efficient functioning and performance of the economy. To achieve financial stability, it is necessary to have in place mechanisms designed to prevent financial problems from becoming systemic or threatening the stability of the financial and economic systems, while maintaining (or not undermining) the economy's ability to sustain growth and perform its other important functions.

The challenge is not necessarily to prevent all financial problems from arising. First, it is not practical to expect that a dynamic and effective financial system would avoid instances of market volatility and turbulence, or that all financial institutions would be capable of perfectly managing the uncertainties and risks

involved in providing financial services and enhancing financial stakeholder value. Second, it would be undesirable to create and impose mechanisms that are overly protective of market stability or that too tightly constrain the risk taking of financial institutions. Constraints could be so intrusive and inhibiting that they could reduce the extent of risk taking to the point where economic efficiency is inhibited. Moreover, the mechanisms of protection or insurance could, if poorly designed and implemented, create the moral hazard of even greater risk taking.

Maintaining the economy's ability to sustain growth and perform its other important functions is an important aspect of the challenge of financial stability. The achievement and maintenance of financial stability should be balanced against other, perhaps higher-priority objectives such as economic efficiency. This reflects the notion that finance is not an end in itself, but plays a supporting role in improving the economic system's ability to perform its functions.

That the challenge is a balancing act can be seen by considering that the likelihood of systemic problems could be limited in practice by designing a set of rules and regulations that restrict financial activities in such a way that the incidence or likelihood of destabilizing asset price volatility, asset market turbulence, or individual bank failures could be eliminated. This type of stability, however, would be achieved at the great expense of economic and financial efficiency.

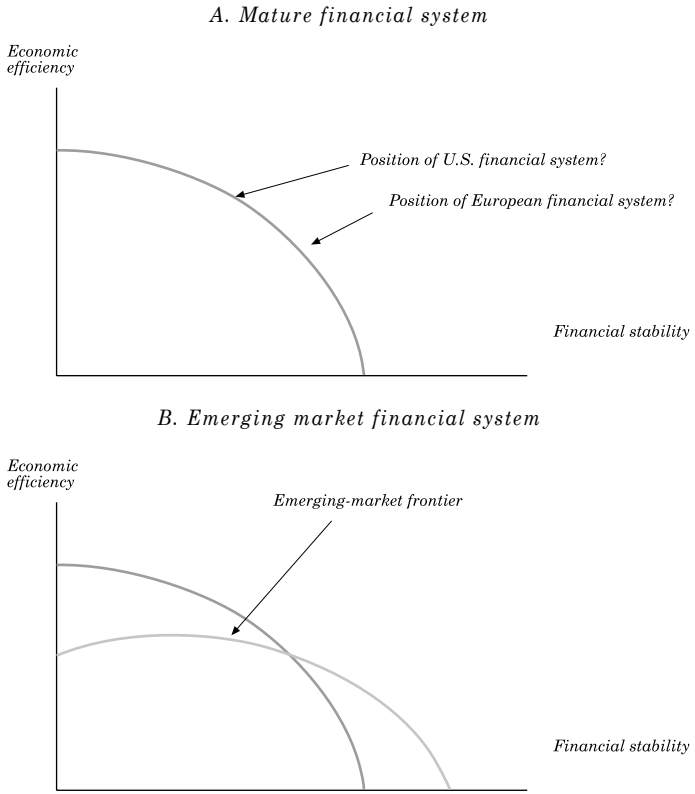
2.3 Stability and Efficiency Are Not Separable

This reasoning leads to the impression, if not conclusion, that there is an ex ante trade-off between achieving economic and financial efficiency, on the one hand, and economic and financial stability, on the other. That is, if one is concerned solely with stability, then it may be possible (though not necessarily desirable) to achieve and maintain it by trading off some efficiency.

The possibility of an ex ante trade-off can be illustrated by narrowing the definitions of stability and efficiency. Consider a market for a good whose price is sensitive to incoming information, a characteristic of many asset markets. In principle, one could limit the variability of the asset price by imposing restrictions in the market that would inhibit the ability of traders to price in every small piece of information. But from a trader's and investor's perspective, such restrictions could inhibit the efficiency of the market's ability to price and allocate resources in the presence of uncertainty.

On the other hand, it is possible to try to maintain efficiency, and even enhance it, while still allowing the financial system room to innovate, evolve, and better support the economic system. If the cost of doing so is greater asset price volatility or capital flow volatility, it is up to society to choose a point along this continuum of trade-offs (figure 1).

Figure 1. Efficiency and Stability Frontiers



Source: Author's drawing.

Some have characterized the difference between the American financial system and the European financial system as choices of different points along this continuum of trade-offs. The American system is more market oriented in that the financing of both household and corporate activities is accomplished more through markets than

in Europe, where there is much greater reliance on bank funding and less reliance on tradable securities (although this is changing). While one might argue that the American system of finance has led to greater economic productivity and efficiency, this greater efficiency is accompanied by greater asset market volatility and turbulence and a greater observed propensity to financial stress.

From a broader perspective, the challenge of achieving and maintaining financial stability goes well beyond the stability of asset prices, or of prices generally. This is not to say that authorities, and central banks in particular, should not be concerned with asset price volatility, and price volatility more generally, because they determine the value of money. Instead, the challenge of financial stability is broader than, and in fact encompasses, the need to limit the impact of price instability on the functioning of the overall financial system. If the financial system is stable, it will be able to tolerate higher levels of asset price volatility as well as other financial problems, including weaknesses in financial institutions.

At the highest level of generality, the challenge of safeguarding financial stability is to have in place a framework for managing the risk of a systemwide problem. There is as yet no international agreement on what such a framework might be, and policymakers always seem to be trying to prevent the last crisis. In other words, there is much work yet to be done to establish an agreed and flexible framework for safeguarding financial stability against the kind of imbalances that surfaced last summer and that led to the ongoing global systemic crisis.

3. Required Conceptual Elements of a Framework

A financial system performs several key functions that foster and support the effectiveness of the real economy: matching savers with investors; pricing and allocating financial resources and risks; and sustainably facilitating various intertemporal economic processes such as wealth accumulation, economic growth, and social prosperity.

It is difficult to reasonably and practically justify an operationally useful definition of financial stability and a framework for safeguarding it that does not acknowledge and incorporate these key functions as core elements. Nevertheless, the economics and finance professions—both policy oriented and academic—have yet to form a consensus on either a definition or a conceptual framework

for formulating financial system policies. This subsection addresses these and related issues by discussing the important conceptual elements that could usefully help the professions safeguard financial stability. The discussion necessarily entails defining terms and examining their implications.

3.1 Toward a Framework

A framework for financial stability can best be understood as a set of definitions, concepts, and organizing principles that impose discipline on the analysis of the financial system. An important component of a framework for safeguarding financial stability is the early identification of risks and vulnerabilities that might threaten the maintenance of stability.

An effective framework would seem to require three important standards. First, there must be rigorous definitions and understanding of key concepts, such as what is meant by the terms financial system, financial stability and instability, and systemic risk, just to name a few. Second, to be most useful for monitoring and policy, the framework's concepts and definitions ultimately must be either directly measurable or correlated with measures: in other words the concepts and definitions must have useful and policy-relevant empirical counterparts. Third, the set of definitions, concepts, and organizing principles, along with their empirical counterparts, must serve the purpose of ensuring internal consistency in the identification of sources of risks and vulnerabilities and in the design and implementation of policies aimed at resolving difficulties should they emerge.

It is important to define the relevant concepts appropriately, especially financial stability, the financial system, and systemic risk.

3.2 Defining Financial System

Broadly, the financial system can be seen as comprising three separable but closely related components. First, there are financial intermediaries that pool funds and risks and then allocate them to their competing uses. Financial institutions increasingly provide a range of services beyond the traditional banking services of taking deposits and making loans, while institutions such as insurance companies, pension funds, hedge funds, and financial-nonfinancial hybrids (such as General Electric) supply a range of financial

services. Second, there are financial markets that directly match savers and investors, for example, through the issuance and sale of bonds or equities directly to investors. Third, there is the financial infrastructure, which includes both privately and publicly owned and operated institutions (such as clearance, payment, and settlements systems for financial transactions) and monetary, legal, accounting, regulatory, supervisory, and surveillance infrastructures.[3]

Both private and public persons participate in financial markets and in vital components of the financial infrastructure. Governments borrow in markets, hedge risks, operate through markets to conduct monetary policy and to maintain monetary stability, and own and operate payment and settlement systems. Accordingly, the term financial system encompasses both the monetary system, with its official understandings, agreements, conventions, and institutions, and the processes, institutions, and conventions of private financial activities.[4] Any analysis of how the financial system works and how well it is performing its key functions requires an understanding of these components.

From this definition, one could reasonably expect that financial stability and monetary stability are related in some meaningful ways. These relationships will become more transparent in what follows.

3.3 Defining Financial Stability

As yet, no consensus has been reached on a useful working definition of financial stability. Some authors define financial instability instead of stability.[5] Others prefer to define the problem in terms of managing systemic risk rather than as maintaining or safeguarding financial stability.[6] Consistent with some aspects of these alternative definitions, I propose and analyze a definition of

3. On the role of the legal system, see, for example, Levine (1999), Leahy and others (2001).

4. This particular formulation is an adaptation of the international financial system in Truman (2003).

5. See, for example, the definitions of Central Bank of Norway (2003), Chant (2003), Crockett (1996), Deutsche Bundesbank (2003), Duisenberg (2001), Ferguson (2002), Foot (2003), Large (2003), Mishkin (1999), Padoa-Schioppa (2003), Schwartz (1986), and Wellink (2002), which are surveyed in Schinasi (2004a, 2006). Davis (2002) develops a typology of instability.

6. From a policy perspective, a positive approach focusing on financial stability is more useful than a negative one focusing on financial instability (see Schinasi, 2006, pp. 91–3).

financial stability that has three important characteristics (Schinasi, 2004a, 2004b, 2006). First, the financial system is efficiently and smoothly facilitating the intertemporal allocation of resources from savers to investors and the allocation of economic resources generally. Second, forward-looking financial risks are being assessed and priced reasonably accurately and are also being relatively well managed. Third, the financial system is in such condition that it can comfortably, if not smoothly, absorb financial and real economic surprises and shocks. If any one or a combination of these characteristics is not being maintained, then it is likely that the financial system is moving in the direction of becoming less stable, and at some point it might exhibit instability. For example, inefficiencies in the allocation of capital or shortcomings in the pricing of risk can compromise future financial system stability by laying the foundation for imbalances and vulnerabilities.

All three aspects of this definition entail both endogenous and exogenous elements. For example, surprises that can impinge on financial stability can emanate both from within and from outside the financial system. Moreover, the intertemporal and forward-looking aspects of this particular way of defining financial stability serve to emphasize that threats to financial stability arise not only from shocks or surprises, but also from the possibility of disorderly adjustments of imbalances that have built endogenously over a period of time—because, for example, expectations of future returns were misperceived and therefore mispriced.[7]

Defining financial stability in this way has several important implications. First, judgments about the performance of the financial system entail how well the financial system is facilitating economic resource allocation, the savings and investment process, and ultimately economic growth. There are two-way linkages: the real economy can be positively or negatively affected by the financial system, and the performance of the financial system can be affected by the performance of the real economy. For a framework to be useful for assessing financial stability, it must pay attention to these linkages. Disturbances in financial markets or at individual financial institutions need not be considered threats to financial stability if they are not expected to damage economic activity at large. In fact,

7. That financial stability should not be thought of simply as a static concept of shock absorption capacity is emphasized by Minsky (1982) and Kindleberger (1996), among others.

the incidental closing of a (minor) financial institution, a rise in asset price volatility, and sharp and even turbulent corrections in financial markets may be the result of competitive forces, the efficient incorporation of new information, and the economic system's self-correcting and self-disciplining mechanisms. By implication, in the absence of contagion and a high likelihood of systemic effects, such developments may be viewed as welcome from a financial stability perspective. Just as in Schumpeterian business cycles, where the adoption of new technologies and recessions have both constructive and destructive implications, a certain amount of instability can be tolerated from time to time because it may encourage long-term efficiency in the financial system.[8]

Second, financial stability is a broad concept, encompassing the different aspects of the financial system, including infrastructure, institutions, and markets. Because of the interlinkages between these components, expectations of disturbances in any one component can affect overall stability, requiring a systemic perspective. Consistent with the definition of the financial system, at any given time, stability or instability could be the result of either private institutions and actions or official institutions and actions, or both simultaneously or iteratively.

Third, financial stability implies not only that the financial system adequately fulfills its role in allocating resources, transforming and managing risks, mobilizing savings, and facilitating wealth accumulation and growth, but also that within this system, the flow of payments throughout the economy functions smoothly (across official and private, retail and wholesale, and formal and informal payment mechanisms). This requires that money—both central bank money and its close-substitute, derivative monies (such as demand deposits and other bank accounts)—adequately fulfills its role as a means of payment and unit of account and, when appropriate, as a (short-term) store of value. In other words, financial stability and what is usually regarded as a vital part of monetary stability overlap to a large extent.[9]

Fourth, financial stability requires the absence of financial crises and the ability of the financial system to limit and deal with the emergence of imbalances before they constitute a threat to stability.

8. See Schumpeter (1934).

9. See Padoa-Schioppa (2003) and Schinasi (2003) on the role of central banks in financial stability.

In a well-functioning and stable financial system, this occurs in part through self-corrective, market-disciplining mechanisms that create resilience and that endogenously prevent problems from festering and growing into systemwide risks. In this respect, there may be a policy choice between allowing market mechanisms to work to resolve potential difficulties and intervening quickly and effectively (through liquidity injections via markets, for example) to restore risk taking or stability. Thus, financial stability entails both preventive and remedial dimensions.

Finally, financial stability can be thought of as occurring along a continuum, reflecting different possible combinations of conditions of the financial system's constituent parts. An analogy is the health of an organism, which also occurs along a continuum. A healthy organism can usually reach for a greater level of health and well-being, and the range of what is normal is broad and multidimensional. In addition, not all states of unhealth (or illness) are significant, systemic, or life threatening, and some illnesses, even temporarily serious ones, allow the organism to continue to function reasonably productively and return to a state of health without permanent damage. One implication of seeing financial stability in this way is that maintaining financial stability does not necessarily require that each part of the financial system operates persistently at peak performance; it is consistent with the financial system operating on a spare tire from time to time.[10]

The concept of a continuum is relevant because finance fundamentally involves uncertainty, is dynamic (meaning it is both intertemporal and innovative), and is composed of many interlinked and evolutionary elements (such as infrastructure, institutions, and markets). Accordingly, financial stability is expectations based, dynamic, and dependent on many parts of the system working reasonably well. What might represent stability at one point in time might be more or less stable at some other time, depending on other aspects of the economic system such as technological, political, and social developments. Moreover, financial stability can be seen as being consistent with various combinations of the conditions of its constituent parts, such as the soundness of financial institutions, financial markets conditions, and effectiveness of the various components of the financial infrastructure.

10. See Greenspan (1999).

3.4 Defining Systemic Financial Risk

According to a report on financial consolidation and risk by the Group of Ten (G-10), "Systemic financial risk is the risk that an event will trigger a loss of economic value or confidence in, and attendant increases in uncertainly about, a substantial portion of the financial system that is serious enough to quite probably have significant adverse effects on the real economy. Systemic risk events can be sudden and unexpected, or the likelihood of their occurrence can build up through time in the absence of appropriate policy responses. The adverse real economic effects from systemic problems are generally seen as arising from disruptions to the payment system, to credit flows, and from the destruction of asset values" (Group of Ten, 2001, p. 126). The G-10 study notes that this definition encompasses much of what is in the literature, but it is stricter in two respects. First, the negative externalities of a systemic event extend into the real economy, rather than being confined to the financial system. Second, this extension into the real economy occurs with relatively high probability. The emphasis on real effects reflects the view that it is the output of real goods and services and the accompanying employment implications that are the primary concern of economic policymakers. "In this definition, a financial disruption that does not have a high probability of causing a significant disruption of real economic activity is not a systemic risk event" (p. 126).

Taken together, a good understanding of what is meant by financial stability and financial instability can serve to define boundaries around the scope of the analysis. The safeguarding of financial stability should not be understood as a zero tolerance of bank failures or as an avoidance of market volatility, but it should seek to prevent financial disruptions that lead to real economic costs.[11]

4. A Framework for Assessing Financial Stability

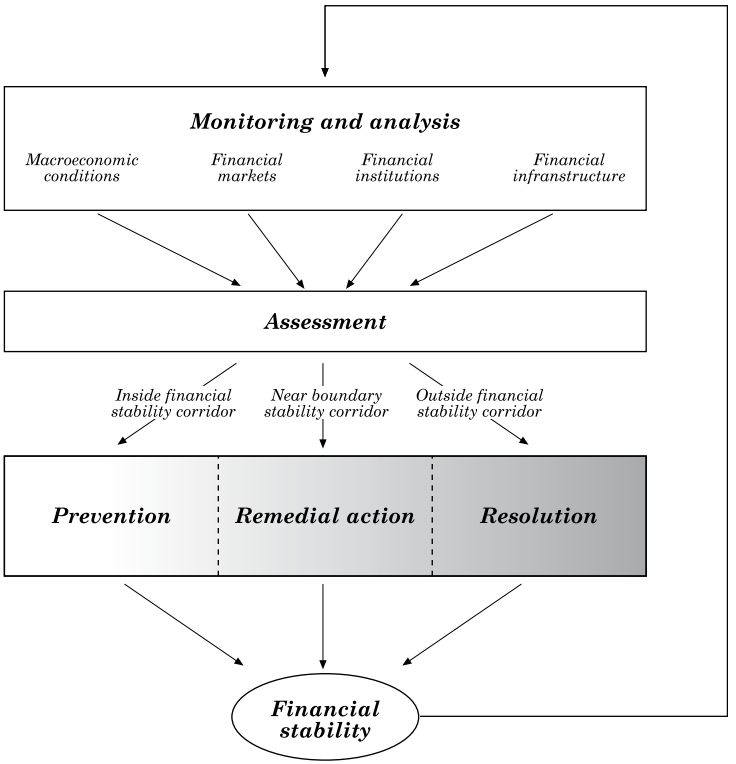
With working definitions of the financial system, financial stability, and systemic risk in hand, it is now possible to discuss the key role of financial stability assessments in safeguarding financial stability. A key to safeguarding financial stability is the early identification of risks to stability and potential sources of vulnerability in the financial system before they lead to unsustainable and potentially

11. Papers that focus on aspects of systemic risk include de Bandt and Hartmann (2000), Hoelscher and Quintyn (2003), and Summer (2003).

damaging imbalances and consequences. For example, weaknesses and vulnerabilities could exist in any of the components of the financial system—namely, institutions, markets, and infrastructure—and could entail all three simultaneously. Along with identifying potential sources of risks and vulnerabilities, it is also desirable to attempt to calibrate their intensity and potential for (or probability of) leading to financial system problems and possible systemic effects. Financial stability assessments are a key part of prevention.

Figure 2 presents a schematic of a reasonable framework for assessing financial stability. Both prevention and resolution of financial imbalances are part of the framework.

Figure 2. Framework for Maintaining Financial System Stability



Sources: Schinasi (2006); Houben, Kakes, and Schinasi (2004).

To prevent financial imbalances from occurring or becoming significant enough to pose a risk to financial stability, the approach taken should entail a continuous process of information gathering, technical analysis, monitoring, and assessment. Because of the linkages between the real economy and the financial system, and also between the various components of the financial system, this continuous process would be most useful if it encompassed both economic and financial dimensions, together with institutional knowledge about institutions, markets, and the financial infrastructure. In effect, the process needs to be comprehensive and analytical (see the top bar in figure 2). Finally, ongoing and fundamental research into the changing structure of the financial system and its changing linkages to the real economy, as well as the further development of measurement techniques for detecting growing imbalances and calibrating risks and vulnerabilities, are vital for keeping this important monitoring phase up to date.

The process entails gathering information about, and monitoring, the macroeconomy (and at times microeconomic aspects, as well) and the various aspects of the financial system through supervisory, regulatory, and surveillance mechanisms. Each of the financial system monitoring components could entail both macro- and microprudential characteristics. For example, when it comes to gathering information about and monitoring individual institutions, the supervisory process could be aided by knowledge about where the economy is along the business and credit cycles and how markets have been performing overall, because the macroeconomy and markets provide the background against which the operational performance of individual institutions should be assessed. Likewise, an assessment of the condition of financial markets must take into account whether the major institutions operating in the markets were well capitalized and profitable. This is another way of observing that there are tradeoffs in safeguarding financial stability, even in the assessment process.

The reason for gathering information, analyzing it, and continuously monitoring the various components of, and influences on, the financial system is to make systematic and periodic assessments of whether the financial system is performing its main functions well enough to be positioned within a corridor of financial stability along the continuum discussed earlier. Such an assessment could lead to three conclusions, which have quite different implications for action (see the middle bar in figure 2, labeled assessment). The assessment might determine that the financial system is within a zone or corridor of

financial stability, approaching a boundary of stability and instability, or outside a zone or corridor of stability. Within the third category, the financial system could further be in a position in which self-corrective processes and mechanisms are likely to move the system back toward the corridor of stability or, alternatively, to need prompt remedial or even emergency measures to reverse the instability.[12]

One could also develop a delineation of financial conditions and potential difficulties according to their intensity, scope, and potential threat to systemic stability. For example, potential financial difficulties can be thought of as falling into one of the following fairly broad categories: difficulties in a single institution or market that are not likely to have systemwide consequences for either the banking or financial system; difficulties that involve several relatively important institutions involved in market activities, with some nontrivial probability of spillovers and contagion to other institutions and markets; and problems that are likely to spread to a significant number and types of financial institutions and across usually unrelated markets for managing liquidity needs, such as forward, interbank, and even equity markets. Problems occurring within these categories would require different diagnostic tools and policy responses, ranging from doing nothing to intensifying supervision or surveillance of a specific institution or market, to liquidity injections into the markets to dissipate strains, to interventions into particular institutions.

4.1 Practical Challenges in Implementing an Assessment Framework

While categories of possible assessments may be easy to discuss in principle, they are difficult to identify in actual practice. How should the boundary of stability be defined and measured, for example? When does an isolated small problem threaten to become a systemic one? There would also seem to be a bias toward being prudent, leading authorities to overreach in identifying both potential sources of risks and vulnerability and to overestimate their likelihood and importance. Thus, it would be useful to establish some ground rules or guidelines for disciplining the continuous process of information gathering, analysis, and monitoring, and identifying sources of

12. As Kindleberger (1996) puts it, "markets work well, on the whole, and can normally be relied upon to decide the allocation of resources and, within limits, the distribution of income, but… occasionally markets will be overwhelmed and need help."

risk and vulnerability. A check list of disciplining principles for identifying risks and vulnerabilities and for assessing where along the stability spectrum the financial system might be could include the following:[13]

—Is the process systematic?

—Are the risks identified plausible?

—Are the identified risks systemically relevant?

—Can linkages and transmission (or contagion) channels be identified?

—Have risks and linkages been cross-checked?

—Has the identification of risks and the assessment been consistent over time?

In practice, the process of assessing financial stability entails a *systematic* identification and analysis of the sources of risk and vulnerability that could impinge on stability in the circumstances in which the assessment is being made. For example, consider the comprehensive list of sources of risks in table 3. An operationally significant distinction is made between endogenous sources of risk that are present within the financial system and exogenous sources of risk that might emanate from outside the realm of finance.

In keeping with the broad definition of the financial system outlined above, endogenous sources of risk can arise in financial institutions, financial markets, infrastructures, or any combination thereof. For instance, credit, market, or liquidity risks may be present in financial institutions, and, if they materialize, they could hamper the process of reallocating financial resources between savers and investors. Financial markets can be a source of endogenous risk not only because they offer alternative sources of finance to nonfinancial sectors, but also because they entail systemic linkages between financial institutions and, more directly, between savers and investors. Financial infrastructures are also an important endogenous source of risk, in part because they entail linkages between market participants, but also because they provide the institutional framework in which financial institutions and markets operate.

Outside the financial system, the macroeconomic environment can be an exogenous source of risk for financial stability because it directly influences the ability of economic and financial actors (namely, households, companies, and even the government) to honor their financial obligations. Financial stability assessments

13. These ideas and concepts are developed in detail in Fell and Schinasi (2005).

Table 3. Sources of Risk to Financial Stability

Endogenous	*Exogenous*

Institutions-based:
• Financial risks
  o Credit
  o Market
  o Liquidity
  o Interest rate
  o Currency
• Operational risk
• Information technology weaknesses
• Legal/integrity risk
• Reputation risk
• Business strategy risk
• Concentration risk
• Capital adequacy risk
	Macroeconomic disturbances:
	• Economic-environment risk
	• Policy imbalances
	
	Event risk:
	• Natural disaster
	• Political events
	• Large business failures

Market-based:
• Counterparty risk
• Asset price misalignment
• Run on markets
  o Credit
  o Liquidity
• Contagion	

Infrastructure-based:
• Clearance, payment, and settlement system risk
• Infrastructure fragilities
  o Legal
  o Regulatory
  o Accounting
  o Supervisory
• Collapse of confidence leading to runs
• Domino effects	

Sources: Schinasi (2006); Houben, Kakes, and Schinasi (2004).

should entail a systematic and periodic process for monitoring each of these sources of risks, both individually and collectively by taking account of cross-sector and cross-border linkages. This process should satisfy the list above.

There are also formidable challenges in assessing the strength and robustness of the measures and models calibrating the plausibility and importance of the various risks, and quantitatively appraising

the potential costs should risks materialize. In actual practice, many shortcuts and qualitative judgments must be made to produce an overall assessment.

For most macroeconomic or monetary policy objectives (such as unemployment, external or budgetary equilibrium, and price inflation), there is a widely accepted measurable indicator (or set of indicators) that defines the objective and measure deviations from it, even if still subject to methodological and analytical debate and even controversy. In the case of both macroeconomics and monetary economics, it took twenty to thirty years of practice, trial and error, measurement and modeling development, and fundamental research to accomplish this. As noted in the introduction, financial stability analysis is still in an infant stage of development. Consequently, there is as yet no widely accepted set of measurable indicators of financial stability that can be monitored and assessed over time. In part, this reflects the multifaceted nature of financial stability, as it relates both to the stability and resilience of financial institutions and to the smooth functioning of financial markets and settlement systems over time.[14] Moreover, these diverse factors need to be weighed in terms of their potential ultimate influence on real economic activity. The lack of indicators also reflects the relatively young age of the discipline of financial stability asessment. Because measurement is not yet highly developed, the current practice of assessing financial stability is more an art form than a rigorous discipline or science.

The challenges in measuring financial system stability reach well beyond the challenges of measuring the degree of stability in each individual subcomponent of the financial system. Financial stability requires that the constituent components of the system—financial institutions, markets, and infrastructures—are jointly stable. Weaknesses and vulnerabilities in one component may or may not compromise the stability of the system as a whole, depending on size and linkages, including the degree and effectiveness of risk sharing between different components. Aggregating information across the system also presents challenges, since different parts of the system perform different tasks. For example, in diversified financial

14. Sets of indicators have been developed, and are widely used, for assessing the soundness of banking institutions. See, for example, core and encouraged sets of soundness indicators in IMF and World Bank (2003) and the IMF's guide on financial soundness indicators (IMF, 2004).

systems, where both financial institutions and markets are important providers of finance, there is no commonly accepted way of aggregating information on the degree of stability in both the banking system and financial markets to form an overall assessment of system stability. If the banking system is functioning well but, at the same time, there are signs of strain in financial markets, the overall assessment of financial system stability is likely to be ambiguous ex ante, particularly if the two components account for similar shares of finance provision. The more complex and sophisticated a financial system, the more complex will be the task of precisely measuring overall stability.

Financial stability assessments carry a higher degree of uncertainty than is ordinarily associated with forecasts based on macroeconometric models. This is because there are formidable practical challenges to measuring, modeling, and assessing the consequences of rare events. First, if past crises were prevented or tackled by policy actions, then the assessment of the likely costs of a selected scenario, based on simulations drawn from historical data sets, will likely be biased unless sufficient account is taken of policy reaction functions. It is doubtful that past policy responses to episodes of financial stress could be summarized by a mechanical reaction function, particularly if the authorities were mindful of avoiding the moral hazards that typically follow from predictable behavior. Moreover, even in cases that did not lead to policy responses, the frequency of crises in historical data sets may be too low to facilitate precision in estimating the likely policy-neutral consequences of a stylized scenario.

Second, confidence intervals around the expected output losses associated with the materialization of a specified scenario may not be well defined statistically—or even defined at all. For instance, simulations based on historical episodes tend to be founded on statistical relationships that reflect the central tendency of probability distributions, rather than the tails. Moreover, for hypothetical scenarios, which have not occurred in the past, it may not be possible to compute a confidence interval around the simulation because the events themselves may be subject to Knightian uncertainty or unquantifiable risk.[15]

Third, most macroeconometric models used for stress testing tend to be built on the basis of log-linear relationships. For simulations, this means that a doubling of the size of a shock will result in a

15. See Knight (1921).

proportionate change in the effect. In reality, however, unpredictable nonlinearities may surface in situations of financial stress, for instance as a result of threshold effects.

Fourth, as witnessed during the near collapse of Long Term Capital Management in 1998, crises may expose unexpected linkages, such as correlations between financial markets that ordinarily tend to be uncorrelated. Given such uncertainties, the real economic costs associated with a particular scenario could well prove to be larger than those predicted by an empirical model. Such considerations would suggest that the output of any stress tests should only be viewed as indicative of how, or if, the financial system would endure adverse disturbances. To avoid complacency, analysts must exercise a high degree of caution and judgment in forming financial assessments.

If the practice of financial stability assessment is to advance from what is essentially an art to a science, progress is necessary on at least three fronts: data, models, and the understanding of linkages. A priority for data gathering must be microeconomic balance sheet data covering financial institutions, households, and firms. While a picture of the aggregate risks borne within each of these sectors can be useful for financial stability analysis, far more important is an understanding of the way in which the risks are distributed across sectors and whether concentrations or pockets of vulnerabilities can be pinpointed. In mature economies, the availability and comprehensiveness of such data are rather mixed, particularly for the household sector.

Two areas where more and better analytical research on financial stability modeling appears necessary include models for identifying risks and vulnerabilities and models for assessing the consequences of adverse disturbances.[16] Concerning the identification of risks, the literature suggests that models are unlikely to ever be capable of predicting crises, particularly in terms of the precise timing. Nevertheless, this should not stand in the way of developing models for assessing vulnerabilities. Even simple, single-indicator approaches can be useful for gauging risks to financial stability (see Campbell and Shiller, 2001), and current work holds promise for the development of more comprehensive frameworks for pinpointing the

16. See Sahajwala and van den Berg (2000) for an overview of early warning systems used by some G-10 authorities; see Persson and Blåvarg (2003) on the use of financial market indicators.

sets of variables (see IMF, 2004) and the conditions that raise the likelihood of financial stress (for example, see Aspachs and others, 2006). As for the prediction of crises, the intellectual advances made in other disciplines in the modeling of complex and discontinuous processes—such as the prediction of earthquakes—may offer insights for financial stability assessment.

5. Concluding Observations

The ongoing crisis reveals that the framework in place prior to the summer 2007 was inadequate for safeguarding the stability of the global financial system against a systemic threat emanating from both the real and financial economies around the globe. All lines of defense against imbalances growing to systemic proportions were breached, and they collectively failed to work as intended or hoped. This applies to both private and official lines of defense against systemic threats to stability, as outlined earlier in the paper.

Once stability is restored and short-term emergency measures are reversed, an important fundamental remaining challenge is for the international community to agree on a framework for safeguarding financial stability once it is achieved. This requires a deeper understanding of what financial stability requires and how economic stability depends on the presumption of financial stability. This is not yet fully understood in the academic and policy communities.

It would help to have a consensus of what is meant by financial stability and an agreed framework for safeguarding it. As discussed in this paper, such a framework must entail both the prevention of imbalances from becoming systemic and resolution mechanisms for limiting the damage of systemic problems if they surface. Both aspects of the existing frameworks around the world have proven to be inadequate for containing systemic risk in the modern global financial system.

Success in safeguarding stability will require the development of analytical frameworks for understanding the difficult conceptual and policy challenges in preventing the buildup of systemic risk and dealing with it should prevention fail. Likewise, analytical frameworks are needed for practically monitoring and assessing both financial stability and the financial system's ability to eliminate imbalances as they arise through market-based mechanisms—or ex ante market discipline. If the ability to dissipate imbalances is found wanting, then the system could be seen as either in or about

to experience a state of instability for which remedial actions would be required.

One objective of this paper was to propose some steps for developing a conceptual framework for safeguarding financial stability based on a definition of financial stability. The definition proposed explicitly links the concept of financial stability to that of economic efficiency and stability. In practice, such a definition can be thought of as providing a basis for an analytical framework that explicitly links the performance of the financial system to the performance of the economic system. One of the main weaknesses of current practices is that we do not yet sufficiently understand the linkages between the real and financial economies. This gap in knowledge reflects the economics profession's inability to integrate the analysis of macroeconomic and financial system tendencies. Without significant progress in this dimension, it is unlikely that much long-lasting success will be achieved in safeguarding global financial stability. My hope is that some of the ideas put forward in this paper will help others find practical solutions to some of the important remaining challenges.

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Toward an Operational Framework for Financial Stability: "Fuzzy" Measurement and Its Consequences

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Over the last decade or so, addressing financial instability has risen to the top of national and international policy agendas. Policymakers in general and central banks in particular have been allocating increasing resources to the monitoring of potential threats to financial stability and the elaboration of frameworks to address them effectively. In part, this trend has been driven by the emergence of episodes of financial distress that have derailed, or threatened to derail, the real economy. The major financial earthquake that has engulfed the global financial system since the summer of 2007 is bound to strengthen this trend further (see Borio, 2008).

Despite the efforts made, policymakers are still a long way from developing a satisfactory operational framework. Tellingly, in the financial stability sphere there is nothing like the well established apparatus employed in the pursuit of price stability (Goodhart, 2006).[1] For price stability, over the years central banks

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1. To be sure, challenges in the pursuit of price stability should not be underestimated; and indeed, some of the hardest ones are closely related to financial stability (Borio, 2006).

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have succeeded in establishing a set of procedures and institutional arrangements that command a broad consensus (for example, Nelson, 2008). By contrast, there is no equivalent agreement on the analytics of financial stability and on how best to secure it. Policymakers are still looking for a reliable compass.

A widely recognized challenge in developing an operational framework for financial stability is measurement: can financial stability or its converse, instability, be adequately measured? Can the risk and cost of future financial distress be measured with sufficient confidence? Measurement influences all the elements of the framework. It translates the definition of the goal into an operational yardstick. It shapes the strategy that maps the goal into the instruments. And it has major implications for the institutional setup that implements the framework, most notably for the governance structure that ensures the accountability of policymakers. In particular, the precision or "fuzziness" with which the goal can be measured is crucial.

Taking the measurement challenge seriously, this paper highlights the key issues faced in the elaboration of an operational framework for financial stability and suggests an outline of the most promising way forward. To keep the paper manageable, we focus exclusively on crisis prevention, rather than crisis management and resolution, and on the architecture of prudential arrangements. We thus do not consider several other policies that can have a first-order impact on financial stability, notably monetary, fiscal, and accounting policies.

Our main conclusion is that while the measurement challenge is a tall one, it does not prevent policymakers from edging closer toward an effective operational framework. In the process of reaching this conclusion, we highlight a number of points. First, analytically, it is useful to distinguish financial instability from financial distress (or a financial crisis). We define financial distress as an event in which substantial losses at financial institutions and/or their failure cause, or threaten to cause, serious dislocations to the real economy. We define financial instability as a situation in which normal-sized shocks to the financial system are sufficient to produce financial distress, that is, in which the financial system is fragile. Financial stability is then the converse of financial instability.

Second, it is important to distinguish the two quite distinct roles that measurement performs in an operational framework. One is to help ensure the accountability of the authorities responsible for

performing the task. The other is to support the implementation of the strategy in real time to achieve the goal. These two roles place different demands on measurement. The former calls for ex post measurement of financial instability, that is, for assessments of whether or not financial instability prevailed at some point in the past. The latter puts a premium on ex ante measurement, that is, on assessing whether the financial system is fragile today. Both ex ante and ex post measurement are fuzzy, but the challenges of ex ante measurement are tougher. For ex post measurement, the *past* occurrence of financial distress can provide irrefutable evidence of instability; for ex ante measurement, it is more important to identify the likelihood and costs of *future* financial distress. Failure to appreciate this distinction can result in misleading conclusions about the feasibility and structure of an ideal operational framework.

Third, the performance of ex ante measures of financial instability is generally rather poor, although some measures are more useful than others. Most techniques provide thermometers rather than barometers of financial distress, in that they do not permit its identification with a sufficient lead and confidence. Given current technology, macroeconomic stress tests, while potentially promising, may actually risk lulling policymakers into a false sense of security. By contrast, leading indicators rooted in the endogenous cycle view of financial instability appear better suited to identify general risks of financial distress. These indicators draw on the Minsky-Kindleberger tradition, which sees the gradual buildup of vulnerabilities associated with aggressive risk-taking as sowing the seeds of subsequent strains. The corresponding indicators take market signals as contrarian signals of the likelihood of distress: for example, unusually low risk premia or unusually strong asset prices and credit expansion are taken as harbingers of future financial distress (Borio and Lowe, 2002a, 2002b).

Fourth, any operational financial stability framework would have a macroprudential, as opposed to microprudential, orientation (Crockett, 2000; Borio, 2003a). This orientation is defined by two features that follow from the nature of financial instability. One is a focus on the financial system as a whole, as opposed to individual institutions, paying particular attention to the costs of instability in terms of the real economy. The other is a reliance on a notion of risk that stresses the potentially destabilizing effects of the collective behavior of economic agents, or the endogenous nature of risk. It is precisely this feature that underlies the amplifying mechanisms that

generate financial distress in response to normal-sized shocks. To varying degrees, these two elements are shared by all the analytical approaches to the modeling of financial instability.

Fifth, strengthening the macroprudential orientation of financial regulatory and supervisory arrangements has implications for the calibration of policy tools with respect to both the cross-sectional and time dimensions of aggregate risk in the financial system. In the cross-section—that is, with respect to the treatment of risk at a point in time across firms—it calls for increasing the weight on common exposures relative to institution-specific exposures (that is, on systematic relative to idiosyncratic risk). At present, no such distinction is formally made. In the time dimension—that is, in relation to the evolution of aggregate risk over time—it calls for addressing systematically the so-called procyclicality of the financial system. The term procyclicality refers to the amplifying (or positive feedback) mechanisms that operate within the financial system and between the financial system and the real economy and that can cause financial instability. While most analytical approaches to financial instability point to such mechanisms, the endogenous cycle view highlights their operation in both bad and good times. As a result, it also stresses the need to restrain the buildup in risk-taking during the expansion phase. A more countercyclical orientation of prudential arrangements would be a key way of limiting procyclicality.

Finally, fuzzy measurement shapes a number of features of the operational framework. Given the difficulties in ex ante measurement, the framework should rely as far as possible on rules rather than discretion. Rules put less weight on the real time measurement of the likelihood and cost of future financial distress and can act as more effective precommitment devices for policymakers. In addition, fuzzy measurement, together with the possibility that for long periods the system may be unstable without financial distress actually emerging, also puts a premium on transparent institutional setups. These need to be based on clear mandates that can help ensure the accountability of the authorities in charge.

The paper is organized as follows. The first section defines financial stability and explores analytical approaches to the modeling of instability. The second section discusses in detail the role of measurement, including its purposes, the tools available, and their strengths and weaknesses, illustrating them with the help of simple examples. The third section outlines the most promising way forward for the design of frameworks and highlights the most

pressing analytical questions. In doing this, we draw lessons from the current financial crisis. An appendix examines the recent performance of leading indicators rooted in the endogenous cycle view of instability.

1. Financial (In)stability: Definition and Analytical Perspectives

Ever since financial stability as a public policy objective has risen to prominence, efforts to define it have multiplied. Even so, a generally agreed definition that could be the basis for an operational framework has remained elusive.

Most definitions of financial stability share three useful elements. First, they focus on the financial system as a whole, as opposed to individual institutions. Second, they do not consider the financial system in isolation, but ultimately measure the economic (welfare) benefits and costs in terms of the real economy (economic activity). Third, they make an explicit reference to financial instability, the converse of stability, which is more concrete and observable.

At the same time, differences abound. Some definitions are very broad, including any allocative distortions arising from financial frictions relative to an ideal benchmark (Haldane, 2004); others are more restrictive, focusing on the absence of episodes of acute distress and significant disruptions to the functioning of the system (for example, Mishkin, 1999). Some highlight the robustness of the financial system to external shocks (for example, Allen and Wood, 2006; Padoa-Schioppa, 2003); others cover the possibility that the financial system may itself be a source of shocks (for example, Schinasi, 2004). Some tie the definition closely to the equally common but elusive notion of systemic risk (for example, Group of Ten, 2001; de Bandt and Hartmann, 2000); others avoid it.

For the purposes of developing an operational framework, some definitions are more helpful than others. Broad definitions unnecessarily widen the objective to be pursued by the authorities and hinder accountability. And, as we argue below, definitions that rule out the possibility of the financial system being a source of shocks, at least as normally identified, risk being too restrictive and misleading.

In this paper we will use the following terminology. We define financial distress or a financial crisis as an event in which substantial

losses at financial institutions and/or the failure of these institutions cause, or threaten to cause, serious dislocations to the real economy, measured in terms of output foregone. We define financial instability as a set of conditions that is sufficient to result in the emergence of financial distress/crises in response to normal-sized shocks. These shocks could originate either in the real economy or the financial system itself. Financial stability is then defined as the converse of financial instability.

While the definition is very rough, it provides a reasonable starting point for our analysis. Three characteristics of this definition are worth noting. First, it is pragmatic. This is why the scope is narrowed to the performance of financial institutions. It goes without saying that large fluctuations in asset prices and the exchange rate or problems in the balance sheets of governments, households, and non-financial enterprises can, by themselves, have a sizable impact on output, even if the financial sector is not seriously disrupted. Pure sovereign and exchange rate crises are examples of the genre. Including them, however, would arguably broaden the definition too much from an operational perspective. Financial stability mandates are probably best defined narrowly in terms of the financial sector, so as to avoid broadening the scope of regulation too far.[2]

Second, the definition distinguishes episodes of financial distress as events from financial instability/stability as properties of the financial system. By their nature, properties are harder to identify than events, as they may involve the appeal to a counterfactual. For example, the system can be unstable even if no financial distress materializes for quite some time (see below).

Finally, it is crucial that distress is generated in response to a shock that is not of extraordinary size, as it is unreasonable to expect the financial system to function effectively regardless of the size of the exogenous shocks that hit it (for example, Goodhart, 2006). Moreover, as discussed next, the analytical approaches to financial instability share this characteristic, that is, a normal-sized shock can generate financial distress through the amplifying mechanisms in the system.

2. This does not imply that authorities should not carefully consider the implications of developments outside the financial sector for its stability. Far from it! Moreover, the broader macroeconomic consequences of strains in the balance sheets of other sectors that do not impinge of the financial sector's stability can be taken into account through other policies, not least monetary policy.

1.1 Analytical Perspectives

Analytical approaches to the modeling of financial instability vary widely. They thus have different implications for how to set up operational frameworks to address it. For our present purposes, it is useful to distinguish approaches along three dimensions. The dimensions are defined in terms of whether financial crises/ episodes of financial distress are seen as (i) self-fulfilling or driven by fundamentals; (ii) the result of endogenous financial cycles or of exogenous negative shocks amplified by the system (the endogenous cycle versus exogenous shock-amplification views); or (iii) reflecting mainly shocks to systematic risk factors or idiosyncratic shocks amplified through spillovers across the system.

The first distinction, between crises seen as self-fulfilling or fundamentals-driven, has a long pedigree. One of the most influential models of banking crises sees them as self-fulfilling (for example, Diamond and Dybvig, 1983). In this model, bank runs are driven by the belief that others will run, given that a deposit contract satisfies customers on a first-come, first-served basis. Illiquidity leads to insolvency: banks engage in maturity transformation, and assets can be liquidated only at a cost. Multiple equilibria exist, one in which the crisis occurs and one in which it does not, without any basis for choosing between them.[3] In other models, a crisis can occur only if the value of the assets falls below a certain threshold, and is in this sense driven by fundamentals (threats to solvency) (for example, Gorton, 1988; Chari and Jagannathan, 1988). Unique equilibria can be achieved, for instance, by restricting agents' beliefs (for example, Morris and Shin, 1998; Rochet and Vives, 2004).

The second distinction, between the endogenous cycle and exogenous shock-amplification views of financial instability, is equally long-standing. The prevailing formal literature on financial instability falls overwhelmingly in the shock-amplification category. The models assume a probability distribution for exogenous shocks that, given the rest of the structure of the economy, may result in financial distress if the realization is sufficiently negative (as in the case of a bad harvest or a fall in productivity). By contrast, an older intellectual tradition sees financial distress as the natural result of the buildup in risk-taking over time, owing to self-reinforcing feedback mechanisms

3. Technically, the equilibrium is chosen based on the artificial notion of sunspots, which act as coordinating devices for beliefs.

within the financial system and between it and the real economy. These mechanisms lead to the buildup of financial disequilibria, or imbalances, that at some point inevitably unwind, thereby generating an endogenous cycle. Minsky (1982) and Kindleberger (1996) are the authors most closely associated with this view. The model is fundamentally dynamic, and the financial system itself plays a key role in generating what may appear as the exogenous shock triggering distress (such as a fall in asset prices from unsustainable levels). In fact, the true shock may well have occurred a long time before and would have been positive (for example, a perceived productivity improvement or a financial reform), triggering a boom-bust cycle in the economy. The actual trigger for the unwinding of the imbalances may be exceedingly small and unobservable (for example, a change in mood), given the fragility built up in the system. While the precise timing of the unwinding is unpredictable, its occurrence is not.

As yet, no formal micro-founded model able to satisfactorily capture the endogenous cycle view of instability has been developed. At the same time, several models incorporate elements of the overall picture. These range from those that explain bubbles in asset prices to those that explore the amplification mechanisms that operate within the financial system and between the financial system and the real economy, as a result of the financial frictions inherent in financial contracts.[4] A notable example is the mutually reinforcing link between credit and asset prices that arises from the use of collateral (Kiyotaki and Moore, 1997; Bernanke, Gertler, and Gilchrist, 1999).[5]

The third distinction, between shocks to systematic risk factors—which, by definition, affect exposures that are common across institutions—and idiosyncratic shocks amplified through spillovers, relates to the channels through which the crisis propagates; it is also less clear-cut than the other two. In models that assume that the

4. The literature on bubbles is vast. See Allen and Gale (2000a) for a model that highlights the role of credit in that context. For a recent overview, see Brunnermeier (2001).

5. General equilibrium models with financial frictions that explore the welfare properties of these amplification mechanisms normally dispense with financial intermediaries altogether, considering only the interaction between entrepreneurs and households. Similarly, these models generally do not generate endogenous cycles, but highlight the buildup in risk-taking that makes the system fragile to exogenous shocks that lead to much tighter financing constraints, thereby amplifying business fluctuations. On both of these aspects, see, for example Lorenzoni (2008), Korinek (2008), and references therein. For an alternative approach that generates endogenous cycles, see Suarez and Sussman (1999).

financial sector is a single entity, as many do, no such distinction exists.[6] In those that assume multiple intermediaries, it is sometimes assumed that the original deterioration occurs in a specific institution and is then transmitted elsewhere through knock-on effects, as a result of the balance sheet or behavioral connections that keep the financial system together. This is the case, for instance, of approaches that stress credit chains, payment and settlement system links, or runs triggered by the inability to distinguish solvent from insolvent institutions (for example, Kiyotaki and Moore, 1997; Allen and Gale, 2001; Rochet and Tirole, 1996a, 1996b; Freixas and Parigi, 1998; McAndrews and Roberds, 1995; Aghion, Bolton, and Dewatripont, 1999). By contrast, other approaches highlight a joint deterioration owing to shared exposures, such as through the holdings of the same assets (for example, Cifuentes, Ferrucci, and Shin, 2005; Allen and Gale, 2004). The distinction is less clear-cut than the other two, however, since shared exposures to risk factors can be both direct, through similar claims on the nonfinancial financial sector, and indirect, through balance sheet interlinkages within the financial sector itself.

Beyond the obvious differences, two common characteristics stand out. First, all the approaches stress how aggregate risk is endogenous with respect to the collective behavior of economic agents. This view of aggregate risk contrasts sharply with the way individual market participants regard and measure risk, treating it as exogenous with respect to their actions. Given the assumed structure of the financial system, this collective behavior can amplify small disturbances and generate instability, that is, result in strong nonlinearities in the response of the system. This amplification is the essence of what has come to be known as the procyclicality of the financial system, whereby the financial system, rather than acting as a shock absorber, acts as a shock amplifier and thus exacerbates business fluctuations (Borio, Furfine, and Lowe, 2001; Borio, 2003a). In models that fall in the negative shock-amplification paradigm, these mechanisms by necessity operate only to reduce output; moreover, the existence of asymmetries associated with the bankruptcy constraints means that they are especially powerful. In models in the spirit of the endogenous cycle paradigm, or in which financial frictions are always present, they also operate during the expansion phase.

6. This would apply, for instance, to the systemic interpretation of Diamond and Dybvig (1983), that is, thinking of their bank as a whole banking system, rather than interpreting the model as one of runs on individual banks.

Second, two types of fundamental sources of instability are at work in the various models, either of which is sufficient to produce it. One source is errors in the elaboration of the information available to agents, that is, the assumption that expectations are not rational or model consistent.[7] Most approaches rule out this possibility, given the popularity of the rational expectations assumption in modern economics. By contrast, such errors are clearly implicit, but not required, in variants of the endogenous cycle view, such as those of Minsky and Kindleberger. Rationality of expectations is one, though not the only, reason why financial accelerator mechanisms have persistence-enhancing effects on shocks rather than having a larger, nonlinear impact on output of the boom/bust variety. The other source of instability is the wedge between individually rational and collectively desirable (welfare-enhancing) actions.[8] Its specific manifestations vary with assumptions concerning the information available to economic agents and the types of financial contacts and markets in which they transact. Relevant notions here are coordination failures, (rational) herding, and prisoner's dilemmas. These are the types of mechanism that explain runs on financial institutions, distress sales, or excessive risk-taking in the expansion phase of the financial cycle (for example, Rajan, 1994, 2005).[9]

From a practical perspective, the various approaches have implications for the broad contours of an operational framework. Some are common to all. In particular, all of them suggest strengthening the robustness of the financial system to shocks. An uncontroversial way of doing so is to strengthen the payment and settlement infrastructure—an aspect which is often taken for granted in the models. Another possibility is to improve the information available to economic agents. This could reduce the possibility of errors in its elaboration or limit the risk of unwarranted contagion. Yet another option would be to improve the buffers in the system,

7. Strictly speaking, the issue is undefined in the case of self-fulfilling crises, in which agents do not form expectations over the likelihood of the two types of equilibria.

8. In some models, financial instability is actually welfare enhancing, given the assumptions made; see Allen and Gale (1998). The assumptions concerning the information available to investors or depositors can be key here. For instance, depending on the quality of the signal received, wholesale depositors may either induce effective market discipline (desirable liquidations) or not (inefficient ones) (compare Calomiris and Kahn, 1991, and Huang and Ratnovski, 2008).

9. See Borio, Furfine, and Lowe (2001) for a more detailed discussion and references to the literature.

although their characteristics would very much depend on the details of the models (for example, insurance, capital, and liquidity).

Other implications vary more substantially. The approaches differ significantly in terms of the ability to measure the risk of financial distress in real time. Taken literally, this is impossible if crises are self-fulfilling.[10] An assessment may be conceptually easier in endogenous-cycle models than in those that stress the exogenous shock-propagation paradigm. The approaches also differ in terms of the weight to be placed on different factors in that context, including liquidity or solvency, interlinkages in the financial system, or direct common exposures to systematic risk, separate from those linkages. They also differ in terms of the most promising areas for policy action. Thus, compared with shock-propagation approaches, the endogenous-cycle perspective more strongly highlights the desirability of restraining risk-taking in the expansion phase.

2. Financial (In)stability: Measurement

Any operational framework designed to secure financial stability requires a mapping of the definition of the goal into a measurable, or at least observable, yardstick. Measurement performs two quite distinct roles. One is to help ensure the accountability of the authorities responsible for performing the task. The other is to support the implementation of the chosen strategy to achieve the goal in real time. The former calls for ex post measurement of financial instability, that is, for assessments of whether financial instability prevailed at some point in the past. The latter relies on ex ante measurement, that is, on assessments of whether the financial system is fragile today. While both ex ante and ex post measurement are "fuzzy," the challenges in supporting strategy implementation are tougher.

As a means of ensuring accountability, it is important to distinguish two cases, depending on whether an episode that may qualify as financial distress occurs during the relevant period. If such an episode does take place, ex post measurement difficulties are challenging but manageable. In order to conclude that the system was unstable, policymakers should be able to (i) recognize financial distress ex post; and (ii) reach a judgment that the distress was out of proportion with the original exogenous (unavoidable) shock,

10. More precisely, the likelihood of distress is impossible to measure; the cost given distress is not.

that is, that financial distress was the result of financial instability rather than extreme shocks. Clearly, even this assessment can involve considerable fuzziness. How large should the losses among financial intermediaries and the associated costs for the real economy be before the episode can qualify as financial distress? How large should the shock be? By definition, the answers to both of these questions can only be given with reference to a model of the economy, however rudimentary. Moreover, where should one draw the line between crisis prevention and crisis management? For example, if the authorities intervene in response to the first signs of strain to manage the situation and thereby avoid the failure of institutions (for example, through early recapitalizations or the issuance of guarantees), is that distress or its prevention (see the appendix)? Nevertheless, overcoming this fuzziness should not be too hard.

Ex post measurement is harder if financial distress has not emerged. The main drawback is that the system may actually be unstable (fragile) even if no financial distress has materialized. Episodes of financial distress are rare, and the window during which the system may be fragile without experiencing a financial crisis may last years. As a result, it can be hard to judge how well the authorities are performing for quite a long time. Judging whether the system was unstable during any given recent tranquil period requires policymakers to answer the same kind of counterfactual as for real time implementation, and hence for ex ante measurement: what would have happened had the system been hit by a shock? Or, in the endogenous cycle view of financial instability, were imbalances building up that simply happened not to unwind during the period? In effect, during tranquil periods, the demands on ex ante and ex post measurement are qualitatively equivalent, although requirements in terms of frequency of observation, lead time, and accuracy are lower for the ex post variant.

As a means of implementing the chosen strategy in real time, the requirements on measurement are, on balance, more demanding than for accountability, since ex ante measurement is inevitable. By the time financial distress emerges, it is too late, as the damage is done. The requirements are especially demanding as a basis for discretionary measures designed to take preventive action. In this case, it is necessary to measure the likelihood and cost of future episodes of financial distress in real time with a sufficient lead and confidence. They are less demanding, however, as a basis for the calibration of built-in stabilizers, such as through the indexing of

prudential tools. In this case, measurement can be less ambitious. It can be based on less precise proxies of risks of financial distress as long as the basic direction of the measures is correct. For instance, it would be sufficient to relate prudential measures to rough estimates of the financial cycle, based on some long-term averages (see the next section).

Another way of highlighting the challenges in ex ante measurement is to consider its implications for the properties of measures of financial instability. Ex ante measurement calls for good leading, as opposed to contemporaneous, measures of episodes of financial distress, that is, for good barometers rather than thermometers of distress. Given the lead-lag relationships involved, such measures would also be good thermometers of financial instability; that is, they would be able to capture the financial system's fragility before financial distress actually emerges. A key challenge here is what might be called the paradox of instability: the financial system can appear strongest precisely when it is most fragile. This puts a premium on the policymakers' ability to read the tea leaves correctly (for example, Knight, 2007).

2.1 A Taxonomy

In considering the possible range of measurement tools, it might be helpful to start from what an ideal measure would be. This measure would be the output of a fully structural model of the economy mapping instruments into the goal. More precisely, it could be written as follows:

$$M \leftarrow f\,(X,I,u),$$

where the measure of financial (in)stability, M, is some transformation of the output of a structural model of the economy, $f(.)$, linking a set of variables, X, to policy instruments, I, and exogenous shocks, u. Such a model would permit the ex post identification of financial instability by decomposing the past into shocks and the endogenous response of the system. It could also be used to generate the ex ante probability distribution of outcomes and hence of financial distress, through the simulation of the shocks, or, alternatively, to generate scenarios (that is, trace the behavior of the system conditional on specific shocks). And it could support the design appropriate policies, by showing how the system would behave under different

configurations of the instruments. For example, the tools would ideally generate a metric of the expected cost of financial distress over a specific horizon, combining the likelihood of financial distress with its cost in terms of economic activity. The authorities could then use this measure as the basis for the calibration of both automatic stabilizers and discretionary actions aimed at keeping it within a desired range.

Reality falls well short of this ideal. In fact, it falls well short even of the less ambitious, but more realistic setup that characterizes the world of monetary policymaking, to which those working on financial stability often aspire (for example, Goodhart, 2006). In monetary policy, the quantitative side of the job is much more developed. Policymakers have models that link instruments to the goal (some varying combination of inflation and output) and use them to make forecasts and carry out policy simulations (Nelson, 2008). Typically, a variety of such tools are employed, exploiting their relative strengths and weaknesses in forecasting and policy analysis. The tools are quite helpful in disciplining the inevitable and crucial role of judgment, and they can be used to keep measures of price stability, such as a point-estimate for inflation over a given horizon, within desired ranges. This is the most common approach in inflation-targeting regimes.

The picture is quite different in financial stability analysis. There are no satisfactory models of the economy as a whole linking balance sheets in the financial sector to macroeconomic variables. Even the empirical modeling of financial instability within the financial sector, for given (exogenous) macroeconomic factors, is often very primitive, hardly going beyond rather mechanical exercises with very limited behavioral content (for example, Upper, 2007).[11] If any instrument at all is included in the model, it is the interest rate,

11. The work by Goodhart, Sunirand, and Tsomocos (2004, 2006a, 2006b) provides an interesting exception. These papers theoretically derive general equilibrium models with incomplete markets, heterogeneous agents, and the possibility of endogenous default. Ultimately, however, calibrating and finding computational solutions for the model are the major difficulties. So far this has only been tried for the United Kingdom (Goodhart, Sunirand, and Tsomocos, 2006b) and Colombia (Saade, Osorio, and Estrada, 2007). In both cases, it was only possible to implement a highly stylized model with three different banks, two states of the world (stress and no stress), and two time periods. Even in this case, calibration proved difficult. As Saade, Osorio, and Estrada (2007) explain, some parameters such as policy variables are observed, some can be calibrated using econometric methods, and others, which are at the heart of the model, can only be arbitrarily imposed. Moreover, these models are based on endowment economies, which rules out feedback effects on output.

whose primary function is to achieve price stability. All this makes it virtually impossible to do meaningful risk analysis and policy simulations within a single framework. Policymakers have to fall back on a variety of much more limited quantitative tools that put little discipline on judgment.

In surveying the landscape of such tools, it is useful to classify them along three dimensions. First, how far do the models provide leading, as opposed to contemporaneous, measures of episodes of financial distress? In other words, how far do they act as barometers rather than thermometers of financial distress? This affects the uses to which those measures can be put. Second, how far do the tools take into account, directly or indirectly, the behavioral interactions that underlie episodes of financial distress? Failure to capture such interactions—that is, the endogenous nature of aggregate of risk with respect to collective behavior—can easily lead to underestimating the likelihood of financial distress. Third, how far do the models actually tell a story about the transmission mechanism of financial distress?[12] Being able to tell a convincing story can influence the models' effectiveness in communicating risks and possibly give more confidence in the outputs. However, there is sometimes a trade-off between the granularity and degree of detail needed for story telling and accuracy in measurement.[13]

We focus on tools that are actually used at present in policy institutions. We start with a variety of indicators, ranging from traditional balance sheet variables to more ambitious early warning indicators (EWIs). We then discuss vector autoregressions (VARs), which amount to very simple representations of the economy and could, in principle, perform both risk and policy analysis. We finally consider current systemwide multi-module measurement models, of which macroeconomic stress tests are the prime example. We illustrate the performance of these tools with some representative examples.

12. This is close to the distinction between structural and reduced-form models. The term structural model is often used to refer to models whose parameters are invariant with respect to policy interventions (so-called deep parameters), so that policy simulations can be properly carried out. Given the state of modeling financial stability, this would simply mean setting the bar too high. We return to this issue in the next section, where we briefly discuss the implications for monetary policy of the inability to model financial distress satisfactorily.

13. For example, simple econometric models, such as autoregressive specifications, may outperform the true model of the data-generating process in forecast performance (Clements and Hendry, 1998). However, autoregressive specifications are certainly not granular enough for policy evaluation or communication.

2.1.1 From balance sheet to market price indicators

The simplest type of indicator comprises statistics based on balance sheet items. These would include, for example, measures of banks' capitalization, nonperforming loans, loan loss provisions, items on the balance sheets of households and corporations, and so forth. Most of the so-called financial soundness indicators listed by the International Monetary Fund (IMF) fall in this category (IMF, 2008). National authorities would also have, in addition, data for individual institutions at a more granular level.

At best, these variables can be used as inputs into a richer analysis of vulnerabilities.[14] Crucially, given accounting rules, variables such as loan loss provisions, nonperforming loans, and levels of capitalization are rather backward-looking and, at best, contemporaneous, rather than leading, indicators of financial distress (that is, thermometers rather than barometers). Indeed, profits tend to be rather high, and provisions low, when risk is taken on; the recent experience has been no different in this respect (figure 1). The same is true for variables such as balance sheet and income leverage. In order to become useful from a forward-looking perspective, they need to be embedded in a theory of the dynamics of instability, such as the endogenous cycle view, that links them explicitly to future episodes of financial distress (see below).

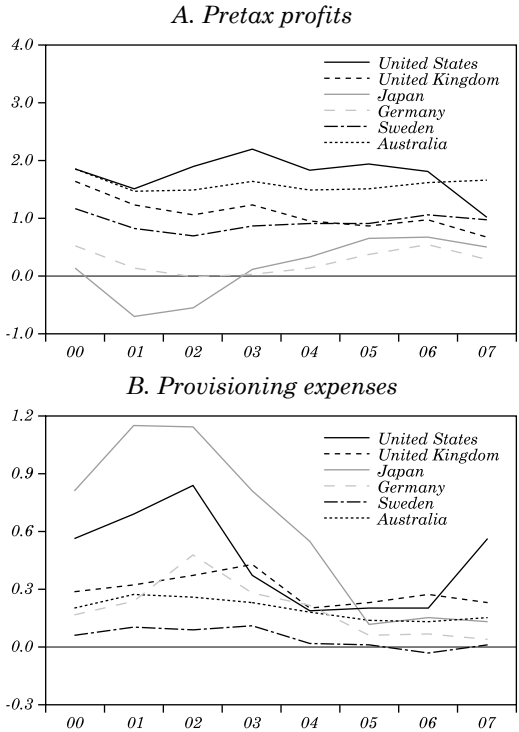
By construction, similar limitations apply to indices that combine balance sheet variables into a single number to generate an index of stress, possibly together with other variables.[15] These indices have the advantage of summarizing a wide set of information into one statistic, which can then be used as an input into a more refined assessment. At the same time, they are not very transparent.

Ratings for individual borrowers go one step beyond balance sheet variables. The ratings could be issued by credit rating

14. A typical process is described in Carson and Ingves (2003) through a so-called transmission map, which traces the impact of possible macroeconomic and financial shocks through the nonfinancial sector on the financial system, as well as the feedback into the real economy. See also Gadanecz and Jayaram (2009), who provide an overview of the use of indicators in current financial stability reports.

15. Bordo, Dueker, and Wheelock (2000) were among the first to aggregate indicators into a single index. Their index is based on four annual series: the bank loan charge-off rates, business failure rates, the (ex post) real interest rate, and the quality spread. To aggregate, they first compute a standardized distance from the median for each variable. The average of the standardized distances is then split into five buckets, from severe distress to euphoria, to generate an index of financial conditions. Similarly, Hanschel and Monnin (2005) build a stress index for Switzerland by aggregating balance sheet variables, such as provisions or capital levels, with market data for banks and confidential supervisory information on the number of problem banks.

Figure 1. Profits and Provisioning
Percent of total assets



Source: BIS annual reports from 2003 to 2008.

agencies or by supervisory authorities, based on more confidential information. Relative to balance sheet variables, ratings have the advantages of combining information into a single statistic and of being designed to be forward-looking. Specifically, they are estimates of the probability of default or expected loss. They have a couple of important limitations, however. First, they relate to individual institutions taken in isolation. Thus, a measure of the strength of the financial system as a whole requires the bottom-up aggregation of ratings that do not take systematic account of common exposures and interactions. Second, their reliability as truly leading indicators of financial distress is questionable, at least in the case of credit agencies' ratings. In practice, downgrades tend to be rather sticky compared with the arrival of information. To a considerable extent, this reflects the fact that such ratings seek to filter out the influence

of the business cycle, that is, to be through-the-cycle rather than point-in-time estimates of default. As a result, they are more helpful in assessing the structural and idiosyncratic determinants of default than in delineating its evolution over time.[16]

An alternative procedure is to build indicators of financial distress from market prices. There are various possibilities. At one end, raw indicators can be considered either in isolation or combined, with little or no theoretical restrictions. Typical variables include volatilities and quality spreads. By imposing some structure, prices of fixed income securities and equities can be used to derive estimates of default probabilities or expected losses for individual institutions and sectors. This requires a pricing model that reverse engineers the various inputs, based on some assumption. For example, so-called expected default frequencies (EDFs, which are basically probabilities of default) can be obtained from equity prices, recalling that equity can be regarded as a call on the firm's assets just as its debt is a put on assets (Merton, 1974). Once again, these individual inputs can then be aggregated, based on some estimates of correlations across the firms' assets, to obtain a measure of distress for the corresponding sector.

On the face of it, such indicators have a number of advantages over those discussed so far. They are forward-looking measures that incorporate all the information available to market participants at a particular point in time, that is, they are comprehensive, point-in-time measures of risk. They therefore implicitly embed views about any common exposures and interactions that may exist within the sector covered. They are also available at high frequencies.

At the same time, they may have drawbacks. Depending on the characteristics of the financial system, their coverage may be too narrow (for example, few institutions may be publicly quoted). Another problem is distinguishing between the market's view of future cash flows and the price it assigns to them, that is, the risk premium. If the purpose is to identify future distress, rather than to determine the price attached to it or to measure current conditions, then the influence of the risk premium should be filtered out. This requires several assumptions and is hard to do with any confidence. More importantly, though, any biases in the market's assessment would be embedded in the estimates. If excessive risk-taking is the

16. In addition, most rating agency assessments include the probability of external support, including government support, in the assessment. From a policy perspective, this should be filtered out. Some ratings seek to do precisely that (for example, Fitch Ratings' individual ratings and Moody's financial strength ratings).

source of financial instability, as some analytical approaches suggest, then estimates of risk derived from market prices would tend to be unusually low as vulnerabilities build up and would tend to behave more like contemporaneous indicators of financial distress.[17]

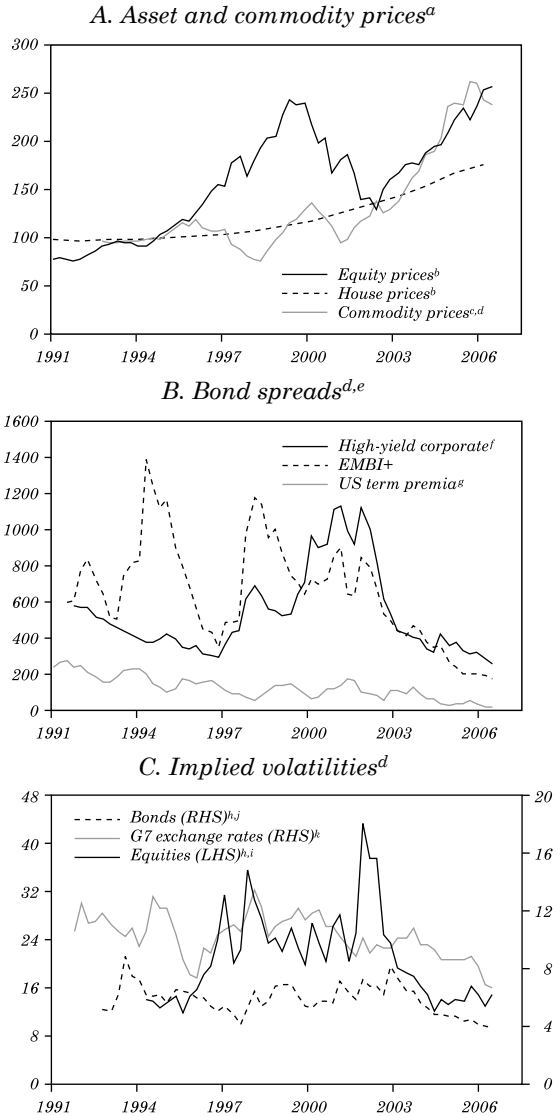
Available evidence tends to confirm that the lead with which market prices point to distress is uncomfortably short for policy. For example, unusually low volatilities and narrow spreads prevailed across a broad spectrum of asset classes until the turmoil started in the summer of 2007, when they then rose sharply (BIS, 2007; figure 2). Figure 3 illustrates this point based on two representative indices of stress, which differ with respect to the degree to which they are constrained by theoretical priors. Figure 3 (panel A) shows an index of stress for the United States based on the methodology developed by Illing and Liu (2006) and first applied to Canada. In essence, the index is a weighted sum of market based indicators for the banking sector, debt markets, equity markets, and liquidity measures. Figure 3 (panel B) plots the price of insurance against systemic distress developed by Tarashev and Zhu (2008); based on banks' credit default swap (CDS) spreads, the index calculates the premium that needs to be paid for insurance against losses that exceed a certain threshold in terms of overall assets of the banks covered with a given probability.[18] As can be seen, both indicators start going up sharply only after the turmoil in financial markets erupted in the second half of 2007.[19]

17. This would reflect a combination of high risk appetite and excessively benign views about future cash flows. To quote Greenspan (2005): "history has not dealt kindly with the aftermath of protracted periods of low risk premiums."

18. Avesani, Pascual, and Li (2006) derive a similar indicator, seeking to estimate the likelihood that more than one bank defaults, based on a latent factor model for an *n*th to default CDS basket. As in the case of Tarashev and Zhu (2008), the indicator refers to risk-neutral probabilities, that is, probabilities weighted by agents' risk aversion. Thus, care should be taken when drawing inferences. An alternative approach is to derive stress indicators based on Merton models for banks (for example, Segoviano and Goodhart, 2007) or the whole economy (for example, Gray, Merton, and Zvi, 2006). Other market-based measures of the likelihood of codistress among banks have been estimated by applying extreme value theory to stock prices (Hartman, Vries, and Streatmans, 2005), the conditional comovement of large abnormal bank stock returns (Gropp and Moerman, 2004), and comovements in value-at-risk measures (Adrian and Brunnermeier, 2007). The basic message highlighted in the text would also apply to these indicators. Some of these measurement approaches have also been run in a stress-testing mode (for example, Xin, Zhou, and Zhu, 2008); see below.

19. Researchers have also developed indicators based on combinations of balance sheet and market price data (for example, Bordo, Dueker, and Wheelock, 2000). Depending on the precise combination and calibration procedures, their properties would lie somewhere in between the two types.

Figure 2. Buoyant Asset Markets

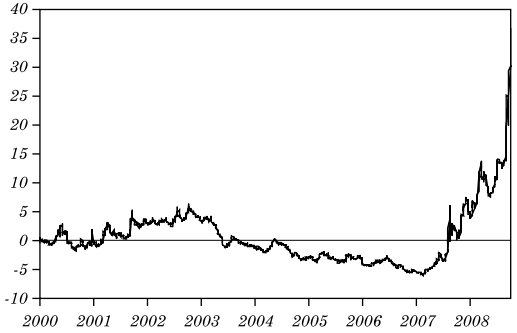


Sources: Bloomberg; Datastream; Merrill Lynch; J.P. Morgan Chase; Organization for Economic Cooperation and Development (OECD); national data.

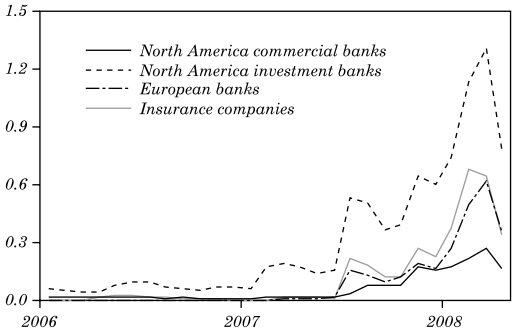
a. 1995 = 100. b. Sixteen OECD countries; weighted averages based on 2000 GDP and PPP exchange rates. c. Goldman Sachs Commodity Index, in U.S. dollar terms. d. Quarterly averages. e. In basis points. f. As of December 1997, simple average of U.S. and euro area high-yield indices; otherwise only U.S. g. Estimated for ten-year zero coupon Treasury bonds. h. Simple average of U.S. and Germany. i. Derived from the price of call option contracts on stock market indices. j. Price volatility implied by the price of call options on ten-year government bond futures contracts. k. J.P. Morgan benchmark index for the level of G7 currencies' implied volatility.

Figure 3. Market Stress Indexes

A. Financial Stress Index for the United States[a]



B. Price of insurance against systemic distress by financial segment[b]



Sources: Bankscope; Datastream; national data; Markit; BIS calculations.

a. De-meaned variance-weighted average (from 1995) of the following indicators: bank bond spread (banks' long-term bond yield against U.S. Treasury bonds), corporate bond spread (corporate long-term bond yield against U.S. Treasury bonds), liquidity spread (three-month U.S. dollar LIBOR against Treasury bills), interest rate spread (long-term U.S. Treasury bond yield against three-month Treasury bills), banks' beta (covariance between bank and total market equity returns / variance of total market returns), and CMAX of equity (index current value / one-year high). For more detailed definitions of individual indicators and different weighting methods, see Illing and Liu (2006).

b. In percent. Based on credit default swap (CDS) spreads for ten commercial and eight investment banks headquartered in North America, 16 universal banks headquartered in Europe, and 14 insurance companies headquartered in the United States and Europe. Risk neutral expectation of credit losses that equal or exceed 15 percent of the corresponding segments' combined liabilities in 2006 (per unit of exposure to these liabilities). Risk neutral expectations comprise expectations of actual losses and preferences.

2.1.2 Early warning indicators

One possible way of overcoming these limitations is to develop formal early warning indicators (EWIs) of financial distress. These are specifically designed to identify episodes of financial distress in advance. There is a growing literature on EWIs. Although most of it was initially concerned with exchange rate and sovereign crises (for example, Berg and Pattillo, 1998), banking crises have been attracting growing attention (for example, Bell and Pain, 2000; Demirgüç-Kunt and Detragiache, 2005; Davis and Karim, 2008). The basic approach consists in using reduced-form relationships linking a set of explanatory variables to a financial distress index.[20] This is generally a zero/one variable, except in Misina and Tkacz (2008), who forecast the Canadian stress index developed by Illing and Liu (2006) using measures of credit and asset prices (see the discussion above).

Potentially, EWIs have some attractive features. They represent statistically rigorous attempts to identify basic relationships in the historical data. They are explicitly forward-looking. They implicitly capture any interactions that have existed in previous episodes. Finally, they might be able to help frame broad stories about the factors behind distress, as long as their structure is not purely data driven, but rather is inspired by some analytical view of distress. True, by construction they can only provide an estimate of the likelihood of distress, not of its costs, but some rough idea of the costs can be derived from those associated in the past with the episodes of distress used in the calibration.

Their performance so far, however, has also revealed a number of shortcomings. The forecasting horizon in often quite short, more relevant for investors than policymakers (for example, typically not exceeding one year and sometimes as short as one month). The prediction may include information that is actually not available at the time the prediction is made (see Kaminsky and Reinhart, 1999). The choice of independent variables may be excessively data driven, so that the story is not obvious and there may be a risk of overfitting at the cost of out-of-sample performance. They have a tendency to produce too many false positives, that is, to predict crises that do not

20. The statistical methodology ranges from threshold models calibrated based on noise-to-signal ratios (Kaminsky and Reinhart, 1999) to multivariate regressions (for example, Demirgüç-Kunt and Detragiache, 1998, 2005). Mixtures of the two are also possible (Borio and Lowe, 2004).

occur, and their performance tends to be rather poor (Bell and Pain, 2000). More generally, there is no guarantee that past relationships will hold in the future.[21]

In research with colleagues, we have sought to develop simple indicators that overcome some of these limitations (for example, Borio and Lowe, 2002a, 2002b). The indicators aim to predict banking crises over horizons ranging from one to four years ahead, depending on the calibration. They rely exclusively on information that is available at the time the predictions are made, so they are truly real-time. They are quite parsimonious, relying on two or at most three variables, as they draw heavily on the endogenous cycle view of financial instability. The basic idea is that the coexistence of unusually rapid credit expansion and asset price increases points to the buildup of financial imbalances that at some point are likely to unwind. The indicators are intended to measure the coexistence of asset price misalignments with a limited capacity of the system to absorb the asset price reversal. Misalignments are simply captured by deviations of asset prices from a (one-sided) trend, while the absorption capacity of the system is captured by deviations of the ratio of private sector debt to GDP from a similar trend, with both exceeding certain thresholds. The precise timing of the unwinding is impossible to predict, so we use flexible, long horizons.

In sample, the performance of these indicators is encouragingly good, with comparatively low noise-to-signal ratios despite their parsimony. This alleviates the false positive problem. As a result, Fitch Ratings (2005) is now using a variant of this methodology to implement a top-down assessment of systemic risks, complementing its bottom-up approach based on individual banks' ratings.

How would those indicators have performed more recently? In the appendix, we take a preliminary shot at this question by extending the indicators to incorporate property prices, based on additional data. We estimate the indicators for a sample of industrial countries over the period 1970 to 2003, and we do an out-of-sample forecast.[22]

A number of conclusions stand out. First, the indicator does identify the emergence of problems in the United States, the country

21. Likewise, they cannot be used consistently to generate counterfactual stories based on alternative policy responses, as they normally do not include instruments. In fact, changes in policy regimes may be one reason why past relationships need not hold in future.

22. See Borio and Drehmann (2009) for a more detailed discussion of the issues raised in the appendix.

at the epicenter of the crisis, with a lead of at least a couple of years. Second, it picks up most of the countries that have taken measures to prop up their banking systems, but it misses those where the problems originated in foreign exposures, in this case to strains in the United States. This highlights an obvious limitation of the indicator in an increasingly globalized world: it is implicitly based on the assumption that the banks resident in one country are only exposed to financial cycles in that country. Third, there are only a couple of cases in which false positive signals are issued, in countries that have seen sizable booms but as yet no financial distress. This last point depends on the specific definition of what constitutes a crisis, which is especially ambiguous in real time, when governments decide to take preemptive measures aimed at forestalling insolvencies or keeping their systems from being at a competitive disadvantage. The global response to the current crisis is quite unique in this regard. Overall, we conclude that despite its obvious limitations, this approach is rather promising as a way of identifying general vulnerabilities associated with credit and asset price booms.

2.1.3 Single-module measures: VARs

In the absence of structural econometric models, vector autoregressions (VARs) could be useful for carrying out stability analysis. VARs are largely data-driven representations of the economy, with few theoretical restrictions. Typically, a rather small set of variables are allowed to interact dynamically, with the dynamics ultimately driven by a set of exogenous shocks. In principle, the tool could be rather versatile if financial distress could be defined in terms of some of those variables (for example, financial institutions' losses exceeding a certain threshold). Through simulations, it can generate a probability distribution of outcomes for the endogenous variables and hence a measure of the probability of distress over any given horizon. For example, the tool could be used to calculate a value-at-risk (VaR) metric for the variable of interest. Alternatively, it could generate the implied value for the variable of interest, conditional on an assumed set of shocks. If the chosen shocks are outside the typical range observed in the sample, this procedure is akin to carrying out a stress test.

In theory, VARs are quite appealing. Depending on the horizon over which the forecasts are made, they can truly act as barometers, rather than thermometers, of financial distress, providing a rich representation of the range of potential outcomes. They take into

account interactions between variables and hence feedback effects. They can also provide the basis for some story telling, tracing the impact of propagation of shocks through the system, although the parameters of the VAR are not amenable to a structural interpretation.

In practice, however, VARs fall well short of this promise. The variables typically used to capture financial distress are rather rudimentary, such as nonperforming loans or defaults in the corporate sector, and poorly modeled. Data limitations are a problem. The representation of the financial sector is cut to the bone, and the range of possible shocks is quite limited, as the models have to be kept manageable for estimation and often exclude asset prices, which are hard to incorporate beyond a general equity price index. The lack of structure implies that the models have very little to say about the dynamics of distress, and the assumptions on which the models are built make it very hard to detect any fundamental nonlinearities associated with financial distress.[23] By construction, given their very nature and the estimation methods, the models capture average relationships among the data series, rather than how the series interact under stress, and they are unable to incorporate boom-bust cycles.

This is illustrated in figures 4 and 5, which show the results of a simple but representative exercise developed by Hoggarth, Sorensen, and Zicchino (2005), who carried out the analysis for the United Kingdom. We replicate it for the United States. The VAR consists of the output gap, nonperforming loans, inflation, and the short-term (three-month) interest rate.[24] Two points stand out. First, as indicated

23. Specifically, the models generally assume that the underlying relationships interact in a (log)linear fashion, so that, say, a three-standard-deviation shock has exactly the same impact as three times a one-standard-deviation shock. This assumption would be acceptable if the underlying data-generating process was linear or the VAR was used to study the impact of small shocks around the equilibrium of the process. However, stress tests do not consider small shocks, and it is not likely that the relevant data-generating processes are all log-linear over the relevant range. Drehmann, Patton, and Sorensen (2006) explore the log-linearity assumption and the impact of large macroeconomic shocks on aggregate liquidation rates in the United Kingdom. While they find that nonlinear models behave significantly differently, they cannot provide strong evidence of feedback effects in their study.

24. The VAR is estimated using quarterly data for the United States from the first quarter of 1990 to the first quarter of 2008, with a lag-length of four. The ordering is nonperforming loans, growth, inflation, and interest rates. Impulse response functions are derived using a Cholesky decomposition. Different unit root tests gave different messages concerning whether nonperforming loans are stationary; for the purpose of this analysis, we assume that they are. As a robustness check we used growth rates in nonperforming loans. In this case, the shape of the impulse response functions is similar, but the effects are even less significant.

by the impulse response functions, the macrofinancial linkages are poorly modeled (figure 4). Nonperforming loans respond only to the interest rate and little to economic slack or inflation. The response of output to nonperforming loans is short-lived, as an easing of monetary policy appears to attenuate the blow. Nonperforming loans are largely determined by their own lagged behavior.[25] Second, just as tellingly, even using an extreme stress-test scenario, we cannot replicate the actual experience with nonperforming loans (figure 5). We assume that a one-off unexpected inflationary shock hits the economy in the first quarter of 2007, raising inflation in that quarter from below 2 percent to 6 percent. This level was last experienced in early 1989. Inflation more than triples within one quarter, compared with an increase of at most 75 percent in any one quarter in the sample starting in 1970. Arguably, such a scenario would never have been run as a "severe, yet plausible" one, something stress tests aim to do. Notwithstanding the severity of the scenario, following an initial rise, nonperforming loans start to drop back to the baseline after one year, given the properties inherent in the VAR model. This type of behavior and results are quite typical for VARs and may explain why, to our knowledge, no central bank uses VARs on their own for the regular assessment of vulnerabilities.

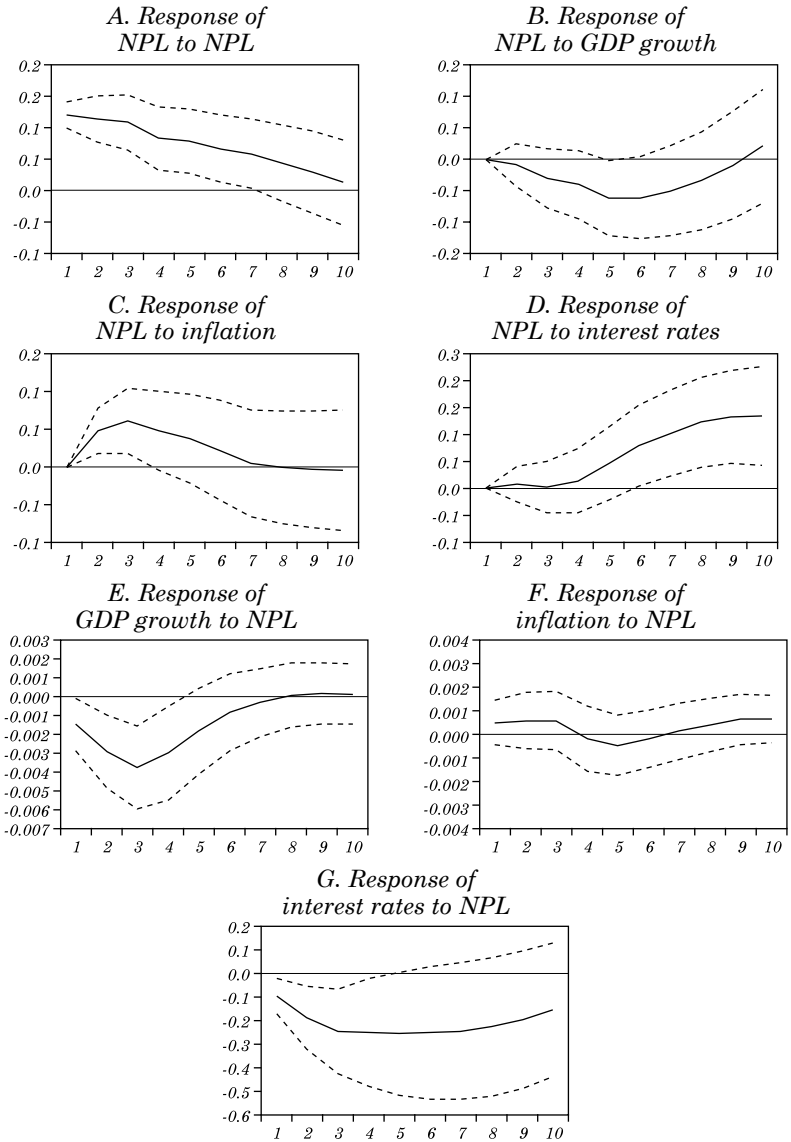
2.1.4 Multiple-module measures: macroeconomic stress tests

The absence of full-fledged structural models and the limitations of VARs have encouraged the use of multiple-module approaches to the assessment of financial distress: so-called macro stress tests generally fall in this category. By analogy with the stress tests for the portfolios of individual institutions, macro stress tests are designed to form a view of how the system as a whole would behave under exceptional but plausible adverse circumstances, that is, in response to negative shocks drawn from the tail of the underlying probability distribution (IMF and World Bank, 2003).[26]

25. Hoggarth, Sorensen, and Zicchino (2005) find some effect of growth on their measure of financial stability (write-offs), but no effect in the opposite direction. Also in a VAR setup, Carlson, King, and Lewis (2008) find that for the United States a higher median EDF for the banking sector depresses the profitability and investment of nonfinancial firms. Aspachs and others (2007) look at a panel VAR of seven countries and find that their measures of financial fragility decrease GDP.

26. This view can take the form of a point forecast conditional on some unusually large shocks or of a whole probability distribution, with its tail representing the outcomes of interest (for example, a value-at-risk measure).

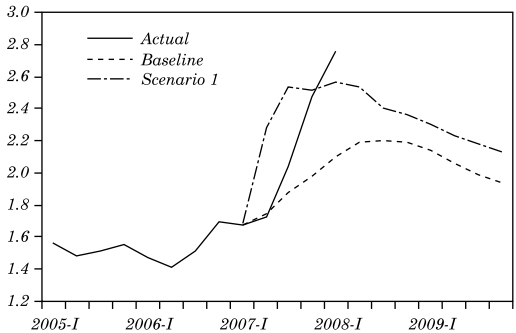
Figure 4. Impulse Response Functions of a Financial Stability VAR for the United States[a]



Sources: National data; BIS calculations.

a. GDP growth: the annual growth rate of real GDP; inflation: annual CPI inflation; interest rates: three-month risk-free nominal interest rate; NPL: the ratio of nonperforming loans to total loans. Impulse response functions are derived using a Cholesky decomposition.

Figure 5. A Simple Stress Test of Nonperforming Loans for the United States[a]



Sources: National data; BIS calculations.
a. NPLRATUS: ratio of no-performing loans to total loans. The baseline mean is the mean forecast of NPLRATUS assuming no shock, starting in the first quarter of 2007. The scenario 1 mean is the mean forecast of NPLRATUS assuming a one-off inflationary shock that increases inflation to 6 percent in the first quarter of 2007. Actual is the actual development of NPLRATUS.

These measures are thus inspired by the negative exogenous shock amplification view of financial instability. They effectively replicate for the financial system the stress tests individual firms carry out on their portfolios.

Despite considerable differences, all macro stress tests share some characteristics (Drehmann, 2009).[27] A macroeconomic engine—whether a VAR (for example, Pesaran and others, 2006), a traditional macroeconomic model (for example, Bunn, Cunningham, and Drehmann, 2005), or a macroeconomic model linked to market risk drivers (Elsinger, Lehar, and Summer, 2006)—is used to generate the shock or to trace out a scenario for macroeconomic variables, that is, the change in the assumed systematic risk factors. These are then used to shock the balance sheets of the relevant sector so as to assess more precisely their impact on its financial strength, measured in a variety of ways (Cihak, 2007). The analogy with banks' own stress tests is obvious.[28] Box 1 illustrates in more detail a couple of examples representative of the range of more advanced practices.

27. For surveys of the range of practices, see Sorge (2004) and Drehmann (2008, 2009).

28. Just as VARs or macroeconomic models draw on the financial accelerator literature, stress tests follow banks' approaches to risk management, which in turn is based on statistical approaches in the tradition of the actuarial sciences (Summer, 2007).

Box 1. Multimodule Measures: Some Sophisticated Examples

One of the earliest multimodule measurement models was developed by Elsinger, Lehar, and Summer (2006) for the Austrian banking sector. It is still the most sophisticated model that is actually fully operational, and it is used to support both regular and ad hoc financial stability assessments. The model integrates market risk, credit risk, interest rate risk, and counterparty credit risk in the interbank sector. The model is able to use a credit register that has a very extensive coverage of on-balance sheet exposures. The model outputs can be represented as loss distributions for the whole financial sector or particular banks or as aggregate VaRs. The model can also be run in stress-testing mode. Importantly, given the information about interbank exposures, the model can trace out how a default of one or more banks can spread through the system.[29] As banks are assumed not to adjust portfolios in reaction to the shocks, the model is always run with a one-quarter (single period) horizon.[30]

Drehmann, Sorensen, and Stringa (2010) are the first to model assets and liabilities simultaneously, in a stress-testing exercise that integrates credit and interest rate risk in the banking book. The approach ensures that banks' balance sheets balance at each point in time during the simulation horizon. While this is a basic accounting identity, it is something all other stress-testing models ignore. Given its granularity, the model provides a suitable framework to explore the impact on banks' profits and losses of different behavioral rules about the investment behavior of banks once assets mature or profits accumulate. Alessandri and others (2009) take this model as one basic building block for a financial stability measurement model for the United Kingdom, which also captures both market risk and counterparty credit risk in the interbank market, albeit very roughly. They also include a simple market liquidity component à la Cifuentes, Ferrucci, and Shin (2005) as an additional feedback channel.[31] Although the model structure could offer an interesting starting point, changes in the investment behavior of banks are not yet linked back to the macroeconomy, so that macroeconomic feedbacks cannot be analyzed.

Macroeconomic feedbacks are the focus of the work by Jacobson, Linde, and Roszbach (2005), who propose a reduced form approach for Sweden

29. Elsinger, Lehar, and Summer (2006) find that the second-round effects associated with counterparty risk in the interbank market are of second-order importance in their model. Joint defaults of banks are mostly driven by common exposures, such as exposure to systematic risk factors.

30. A recent version (Boss and others, 2008) extends the horizon to three years and makes the assumption that all profits are immediately distributed to shareholders. No other reactions are allowed for.

31. The authors show that these feedback effects can be sizable, but this requires very strong and arguably unrealistic assumptions about the market risk component of the model.

consisting of an aggregate VAR model that includes the average default frequency of companies as a measure of financial stability, a model linking macroeconomic and balance-sheet-specific factors to company defaults, and a module linking the evolution of balance sheets in response to macroeconomic factors. By integrating these three building blocks, they show that there are significant feedback effects from financial stability back to the real economy. Given the nonlinear nature of the model, they can also show that the impact of shocks is state dependent. For example, monetary policy seems to be more potent in recessions than in booms. De Graeve, Kick, and Koetter (2008) use the same methodology but can proxy financial stability more directly, as they model the default probability of banks in Germany. They find that bank capitalization has significant implications for the transmission mechanism of shocks to banks' balance sheets and back.[32]

While all these models make important contributions to the stress-testing literature, none is so far able to combine all the elements, because of enormous technical difficulties and a lack of data. Important components missing are off-balance-sheet items and funding liquidity. The former reflect serious data limitations. As for the latter, combining macro stress tests with a marketwide liquidity stress test in line with van den End (2008) could be an interesting starting point, although it is doubtful that extreme reactions as currently observed can ever be captured.

Just like the stress tests for individual institutions, macro stress tests have become quite popular. They are explicitly forward-looking. They have the potential to cover a broad range of scenarios, not constrained by the probability distributions derived in estimation. They are quite helpful in tracing the propagation mechanism from shock to outcome and hence in story telling and communicating concerns. Above all, they can be much more granular than other approaches, relating scenarios to features of individual balance sheets. For example, information about interlinkages in the banking sector can be used to calculate knock-on effects from losses at individual institutions (Elsinger, Lehar, and Summer, 2006). The ultimate measures of distress, therefore, are closer to those that capture the concerns of policymakers, such as the erosion in the degree of capitalization in the banking system.

Even so, their limitations should not be underestimated. Some of these have to do with the shortcomings of the individual modules. As already discussed, the macroeconomic modules do a very poor job of incorporating financial variables, hardly ever going beyond

32. In particular, they find that the impact of a monetary policy shock can be six times larger when the banking system is weakly capitalized.

equity prices and interest rates, regardless of whether VARs or other macroeconomic models are used.[33] Given that the macroeconomic model is the source of all shocks in these applications, episodes of distress that are not driven by macroeconomic factors cannot be simulated. This restricts the use considerably, as events like the current crisis cannot be captured. The relationship between macroeconomic risk factors and credit risk proxies is also often poorly modeled. Additionally, the balance sheets of the financial sector generally exclude important items. For example, given the enormous data requirements, current models are not able to account for off-balance-sheet commitments, an item that has been at the heart of the recent crisis.

Other limitations relate to how the modules are linked. For one, the modular structure can easily result in internal inconsistencies, both conceptual and empirical, such as those that can arise from piecewise estimation.[34] Moreover, there is a clear danger of excessive complexity, undermining robustness and ease of communication, both within the organization and with the public. Most importantly, greater granularity and relevance are bought at the expense of ruling out interactions and feedback effects. After all, these interactions, both within the financial system and between the financial system and the real economy, lie at the heart of the dynamics of financial distress. This is especially serious when the horizon of the simulation exceeds one period, as it realistically should. The very fact that unusually large shocks are needed to produce any action suggests that the current generation of macro stress tests is missing essential elements of financial instability. As a result, there is a serious risk that macro stress tests, as currently carried out, may underestimate the likelihood of financial distress and its potential magnitude.[35]

This is consistent with recent experience. To our knowledge, all the macro stress carried out before the recent financial turmoil failed to anticipate it as a possible relevant outcome. The tests indicated

33. Typical shocks would thus include changes in output, inflation, or, less often, oil prices.

34. An easy-to-make mistake would, for example, be to treat interest rates as an I(1) variable in one module but as an I(0) in another.

35. Moreover, from the perspective of the endogenous cycle view of financial instability, macro stress tests could at best capture the endgame, since by construction they trace out the impact of negative shocks. While this may be very useful in understanding the interaction in the financial system during a crisis and the potential costs, it may be less suited to identifying potential problems with a sufficient lead time for policymakers to react.

that the capital buffers in the system were perfectly adequate, and yet they came under considerable strain once the turmoil erupted.[36]

2.2 An Overall Assessment

The discussion of quantitative measurement tools points to a number of conclusions. First, the technology to measure the likelihood of financial distress in real time is still rather rudimentary. The tools generally provide little comfort in the estimates, and, with rare exceptions, the lead with which distress is assessed is insufficient to take remedial action. Most behave more like thermometers than true barometers of distress and/or risk, lulling policymakers into a false sense of security. At the same time, those EWIs that draw on the endogenous cycle perspective on financial instability appear comparatively more promising.

Second, to our mind, the reasons for this unsatisfactory performance reflect a mixture of factors. For one, financial distress is an inherently rare event. This makes estimation with any degree of confidence very hard, even if the processes at work do not change fundamentally over time. Sufficiently long data series may not be available, and when they are, they typically span different economic structures, which adds to the uncertainty surrounding inferences. The very fact that financial innovation or regime shifts such as financial liberalization are common features of crises heightens uncertainty (box 2). Relying on other countries' experience may help, but it can also generate further doubt. Moreover, the available tools do a very poor job of capturing the interactions and nonlinearities that lie at the heart of financial instability. They are unable to capture its essence, namely, outsized responses to normal-sized shocks. And there is considerable disagreement on what is the best analytical framework to guide the analysis.

Finally, all this implies that the available quantitative tools do not impose sufficient discipline on the judgmental assessments of vulnerabilities routinely carried out in national and international forums (Borio and Shim, 2007). On the one hand, there has been

36. In principle, one could envisage a highly complementary use of EWIs and macroeconomic stress tests (for example, Borio, 2003a). The former can be used to measure the likelihood of distress, the latter its cost conditional on distress. As the above analysis suggests, however, the inconsistencies between the two types of tools does not as yet make this feasible.

an excessive tendency to look at everything without a good sense of just how to look at everything. On the other hand, there is still too much room for quasi-philosophical priors concerning the strength of the stabilizing or destabilizing nature of market forces to influence the final judgments.

Box 2. Financial Liberalization and Innovation: A Problem for Measurement Models

All measurement models discussed rely on historical data to uncover the embedded behavioral relationships. Given this constraint and the typical estimation methods, the models mainly capture average past relationships among the data series, rather than how the series interact under stress. The reliance on past data also implies that these models are not well suited to capturing innovations or changes in market structure. And yet, innovations—be they financial, such as structured credit products, or real, such as the invention of railways—are often at the center of the build-up of imbalances and the following distress. Similarly, it is not uncommon for financial liberalization episodes to trigger a boom that may prove unsustainable while at the same time changing certain characteristics of the economy.[37]

Even though this is rarely done, stress tests can help to challenge the projected risk characteristics of new products where limited or no historical data are available.[38] This requires making assumptions about the behavior of new products. In practice, this implies that the characteristics of new products may be approximated by those of others for which historical information is available. This process involves potential pitfalls.

To illustrate this point, we implement a micro stress test for a portfolio of asset-backed securities (ABS) exposures, following a procedure that was not uncommon prior to the crisis. The typical assumption was to proxy the default characteristics of ABS by those of corporate bonds of the same rating category. Based on this assumption, we implement a severe stress test scenario starting in February 2007.[39] An unspecified

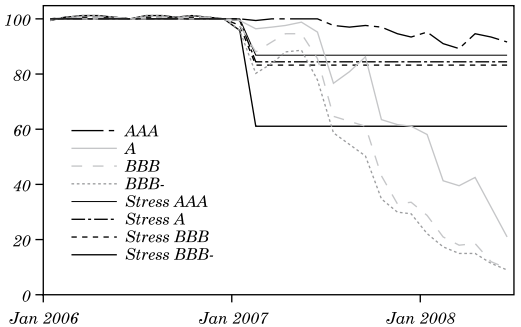
37. The EWIs discussed in box 1 are also subject to the criticism that they rely on historical relationships to predict future crises. However, they seek to focus on factors that past experience indicates have been invariant across policy regimes and periods of financial innovations.

38. See Bunn, Cunningham, and Drehmann (2005) for how this can be done in the context of macro stress testing.

39. Actual price levels are based on the ABX index from J.P. Morgan for the 2006.1 vintage for different ratings. The treatment of correlations is crucial for the pricing and evolution of structured credit products (Fender, Tarashev, and Zhu, 2008). This stress test implements a very simplistic correlation structure. It assumes that defaults occur independently, but price changes are fully correlated.

shock is assumed to lead to defaults in each rating category equal to the highest default rates ever observed for corporate bonds in that category. These are essentially default rates from the Great Depression. In addition, nondefaulted exposures experience a drop in prices that is three times the worst annual return on corporate bond indexes for the various ratings over the period 1990 to the beginning of 2007.

Figure 6. Stress Testing New Products[a]



Sources: J.P. Morgan; BIS calculation.

a. The figure illustrates a simple test that proxies ABS with corporate bonds. ABS tranches are assumed to behave like bonds of the same rating category. The stress test scenario starts in February 2007. An unspecified shock is assumed to lead to defaults in each rating category equal to the highest default rates ever observed for corporate bonds in that category. In addition, nondefaulted exposures experience a drop in prices that is three times the worst annual return on corporate bond indexes for the various ratings over the period from 1990 to the beginning of 2007. Solid lines plot actual market prices for the ABS index from J.P. Morgan for 2006:1 vintage for different ratings. Dotted lines plot the impact of the hypothetical stress test for different ratings. Impact for BBB ratings is worse than for A, but it is hard to distinguish in the figure.

Only for AAA ratings is the outcome of this stress test worse than actual developments, while the impact for all other categories is much more benign. Admittedly, more appropriate pricing models should have fared better. But to replicate actual price developments, given the typical assumptions used at the time, it is likely that rather extreme scenarios would have been needed—something which is arguably not consistent with the stress tests' focus on "severe yet plausible" scenarios.

A more general point is apparent from eyeballing the graph. By definition, only limited data is available for new products and none of that would be taken from a crisis. Understanding the true statistical properties is therefore difficult, if not impossible, from an ex ante perspective. Arguably, measurement models built on these statistical relationships will break down in precisely those scenarios that they aim to capture beforehand—a problem that is present for many financial times series more generally (see also Danielsson, 2008).

3. Toward an Operational Framework: A Way Forward

The above discussion indicates that the analytical basis for an operational financial stability framework is not very satisfactory. The definition of financial (in)stability has a number of agreed elements, but it is not very precise. There is no unified analytical framework that commands a broad consensus. The state of quantitative measurement is poor. As a result, measurement is fundamentally fuzzy.

At the same time, the shortcomings of this analytical basis should not be overstated, especially once the dual role of measurement is acknowledged. Rather, the operational framework should recognize both the known and the unknown elements. Overall, the analysis does point to a number of desirable features that any such framework could have and, by implication, to helpful steps forward. Some of the features are independent of the specific view one may have of the nature of financial instability, while others call for more of a stand on this issue.

3.1 Desirable Features: From Microprudential to Macroprudential

We highlight six desirable features. First, any operational financial stability framework would have a macroprudential, as opposed to microprudential, orientation (table 1; see Crockett, 2000; Borio, 2003a; Knight, 2006). It would focus on the financial system as a whole, as opposed to individual institutions. The failure of individual institutions, regardless of the implication for the system, does not amount to financial instability. The framework would also explicitly treat aggregate risk as endogenous with respect to the collective behavior of institutions rather than as exogenous, as individual economic agents would tend to do. This would help to address the wedge between actions that are rational for individual agents, but that collectively do not result in desirable outcomes.

Second, while distinctions are hard to make within the financial sector, some institutions deserve more attention than others. Institutions that are highly leveraged or engaged in substantial liquidity transformation are more vulnerable than institutions that are not. If they further have large outstanding liabilities, are highly interconnected, or play key roles (such as wholesale payment services or market making in important derivatives markets), then

Table 1. A Comparison of the Macro- and Micro-prudential Perspectives[a]

Trait	*Macroprudential*	*Microprudential*
Proximate objective	To limit distress across the financial system as a whole	To limit distress in individual institutions
Ultimate objective	To avoid output (GDP) costs linked to financial instability	To provide consumer (investor or depositor) protection
Characterization of risk	Dependent on collective behavior (endogenous)	Independent of individual agents' behavior (exogenous)
Correlations and common exposures across institutions	Important	Irrelevant
Calibration of prudential controls	In terms of systemwide risk; top-down	In terms of the risks of individual institutions; bottom-up

Source: Borio (2003a).
a. As defined, the two perspectives are intentionally stylized. They are intended to highlight two orientations that inevitably coexist in current prudential frameworks

their failure would be particularly disruptive for the system as a whole.[40] At the same time, broad coverage is critical. For example, even if individually small, a large set of institutions could raise serious risks for the system as a whole if they are exposed to similar common risk factors. Moreover, the features that make institutions especially relevant for financial stability hardly apply to banks only.

Third, in the cross-section at a given point in time, a macroprudential approach highlights the importance of common exposures across financial firms, that is, exposures to systematic risk.[41] This holds true regardless of whether these exposures are direct, arising from claims on the nonfinancial sector, or indirect,

40. The general point (also noted by Morris and Shin, 2008) is that institutions with a high systemic impact factor deserve special attention or tighter standards owing to the implications of their distress for the system as a whole.

41. For theoretical analyses of the implications for the prudential framework of the distinction between systematic and idiosyncratic risk, including for issues such as diversification, see Acharya (2001) and Wagner (2008, 2010).

reflecting exposures to each other. Other things equal, the higher the exposure to systematic risk, the higher is the threat to the financial system as a whole, as the institution is likely to incur losses at the same time as the other institutions, making it harder to absorb them.[42] This is bound to strengthen the endogenous amplifying mechanisms that generate financial distress and increase its cost for the real economy. As a result, a key principle of the approach is to calibrate prudential tools so as to increase the weight on systematic risk relative to idiosyncratic risk: at present, prudential requirements are generally set based on the overall risk profile of individual institutions, without making any distinction between the two.

Fourth, in the time dimension, the key principle of a macroprudential approach is to dampen the procyclicality of the financial system. This means encouraging the buildup of buffers (for example, in terms of institutions' capital and funding liquidity) in good times, during the expansion phase, so that they can be run down, in a controlled way, as harder times materialize and financial strains threaten to emerge. The buildup of buffers would strengthen the system's resilience to the emergence of incipient distress as long as the buffers were allowed to operate as such. Crucially, this implies a willingness to allow them to be run down, since otherwise they act as minima and become shock amplifiers rather than shock absorbers. In addition, to the extent that it behaved as a kind of dragging anchor, the buildup of buffers could also restrain risk-taking and any balance sheet overextension during the expansion. This, in turn, could mitigate the influence of any incentives to take on risk resulting from the anticipation of public support in the event of systemic distress (moral hazard).[43]

Fifth, the operational framework would rely as far as possible on built-in (automatic) stabilizers rather than discretion. This would help address the limitations in the measurement of aggregate risks in real time, which can make discretionary action error-prone. And it would limit the danger that, even when risks are correctly identified, no action may be taken for fear of going against the manifest view of markets. The widespread failure to anticipate the

42. See, in particular, Hellwig (1995) on the pitfalls of assessing the soundness of institutions in isolation as opposed to in a system context.

43. See Acharya and Yorulmazer (2007) for a formalization of this point.

recent credit crisis and take remedial action, even when general risks were identified, has hammered this message home.[44] Once in place, automatic stabilizers do not require continuous justification, and they can thus act as an effective precommitment device. They leave little room for policy error provided they are linked to robust aspects of the financial cycle and are not too ambitious. Importantly, the corresponding measure need not track systemwide risk perfectly, but just provide a rough gauge. For example, it would be sufficient that the evolution of the stabilizers is related to some robust aspects of financial conditions measured relative to average historical experience (see below).

At the same time, automatic stabilizers and discretionary measures should not necessarily be seen as mutually exclusive. Discretionary measures could complement automatic stabilizers if the latter faced design limitations. Likewise, they might be more easily tailored to the nature of the buildup in risk-taking and vulnerabilities as long as these are identifiable in real time. They may also be harder to arbitrage away, as circumvention becomes easier over time. The key issue would be how to constrain and discipline any such discretion.

Finally, institutionally, any operational financial stability framework would align objectives with the control over relevant instruments and the know-how to use them. This is difficult. Financial stability is a task on which a whole range of policies have a bearing, well beyond prudential policies. Even within prudential arrangements, the institutional setup is often not particularly conducive to an effective implementation of the macroprudential orientation. Not least, mandates tend to have a microprudential orientation. In particular, the presence of depositor or investor protection in the statutes of some supervisory authorities is not easily reconcilable with a systemwide perspective. Moreover, the embedded culture and expertise may not

44. To be sure, signs of building vulnerabilities were not hard to detect, especially if seen from the perspective of the endogenous cycle view of instability. Several observers, including in the official sector, did not hold back warnings to that effect, albeit sometimes in coded or guarded language (for example, BIS, 2005, 2006, 2007; Knight, 2007; IMF, 2007; ECB, 2007; Bank of England, 2007; Geithner, 2007). Even so, there was a general tendency to overestimate the system's ability to withstand shocks and to take comfort from what, on the surface, appeared to be strong levels of capitalization and better risk management practices. Actual policy action to rein in risk-taking was limited, not least out of a concern that tightening prudential standards would inevitably be seen as going against the manifest view of markets.

be sufficient even when the instruments are available.[45] This may be less of an issue where central banks are in charge of supervision, given their natural comparative advantage in macroeconomic issues, but it could be relevant elsewhere, where legal and accounting backgrounds are the rule.

3.2 Next Steps

What are the most promising next steps to edge closer to an effective operational financial stability framework? We consider three aspects in turn: improving the measurement of risk; strengthening the architecture of prudential arrangements; and putting in place an institutional setup that supports the framework. As already noted, we focus only on prevention.

3.2.1 Measurement of risk

The overall objective in risk measurement would be to improve the way low-frequency, systemwide risks are evaluated. Better risk measures could be used not only for the calibration of policymakers' tools, but also as inputs in firms' own risk assessments.

Our analysis suggests a set of priorities in this area. First, analytically, major steps are needed to develop better models of financial instability, marrying micro- and macroeconomic aspects. A priority is to explicitly incorporate endogenous amplifying mechanisms. At present, no such operational models exist. Without them, for instance, there is a serious danger that macro stress tests will lull policymakers into a false sense of security.[46]

Second, for monitoring and calibration purposes, it is important to develop better information about the interlinkages and common exposures in the financial system. As some of this information is bound to be regarded as confidential, it would have to be reported to the authorities and not disclosed publicly (Borio and Tsatsaronis, 2004, 2006).

45. Control over instruments is often imperfect or limited, especially when other types of authorities are involved, such as those responsible for accounting and taxation.

46. These limitations extend to models used for monetary policy. Despite confidence in their performance, their inability to capture the build-up of financial instability and the consequences of the materialization of financial distress can clearly lead policymakers astray (see Borio, 2006).

Finally, for the immediate future, working on EWIs appears more promising than on macro stress tests. We expect improvements in macro stress tests to require considerable time, owing to the analytical and informational demands involved. As long as EWIs are not too ambitious, they can help to highlight general risks to the financial system. Arguably, as suggested by recent empirical evidence, developing indicators that draw on the endogenous cycle view of financial instability is the most fruitful route. These indicators could be refined through better measures of financial system leverage and risk-taking, based on either price or balance sheet information.[47]

3.2.2 Architecture of prudential arrangements

The overall objective in structuring prudential arrangements would be to strengthen their macroprudential orientation, both in the cross-sectional and time dimensions. Consider each in turn. In the cross-section, there are a number of ways of calibrating prudential tools so as to increase the weight on systematic risk relative to idiosyncratic risk. One could deliberately seek to estimate separately the exposures of individual institutions to the two sources of risk; alternatively, simpler proxies could be used based on the composition of balance sheets.[48] Similarly, for a given exposure to systematic sources of risk, institutions whose distress had a larger impact on

47. Our analysis also points to a potentially serious limitation of this work as an input into individual firms' own risk assessments, in that they are even more vulnerable to two shortcomings than policymakers' assessments (Borio, Furfine, and Lowe, 2001; Lowe, 2002). First, they make no attempt to endogenize risk with respect to the collective behavior of economic agents. Second, they tend to focus on short horizons; in the case of banks, for instance, horizons range from a few days for trading books to at most one year for loan books, making it more likely to assume the continuation of current conditions. These shortcomings can easily lead to highly procyclical risk measures that underestimate systemwide risk and its repercussions on the firms' own balance sheets. The problem here is that even if improvements in risk measurement technology were achieved, distortions in incentives of individual firms would remain. They would hinder the lengthening of the horizon and could induce them to target levels of risk tolerance and risk-taking that, from the perspective of the system as a whole, could be inappropriate.

48. An example of the former comprises statistical techniques designed to measure the sensitivity of an institution's return on assets to common risk factors. An example of the latter includes balance sheet exposures to sectors/industries (for example, real estate) and types of particularly cyclically sensitive activities (for example, leveraged buyouts). For example, tighter prudential standards or concentration limits could be applied on that basis.

the system as a whole would also be subject to tighter standards, given their importance as sources of indirect exposures in the system. Size is one relevant factor.[49] Building on existing arrangements, the increased weight on systematic risk could be achieved through transparent adjustments in the calibration of current prudential tools specifically designed to capture this aspect (what might be termed a macroprudential overlay).

In the time dimension, there are several options to address the procyclicality of the financial system through the offsetting behavior of prudential cushions. As this has been extensively discussed in other work (for example, Borio, Furfine, and Lowe, 2001; Borio, 2003a; Borio and Shim, 2007), we highlight only a number of general considerations here. First, a holistic approach is needed. A broad range of policies have an impact on the procyclicality of the system. Thus, the required adjustments in the prudential framework will depend on the characteristics of other policies and on any adjustments made to them. For example, the current trend toward fair value accounting is likely to add to procyclicality by making valuations more sensitive to the economic cycle, as it embeds evolving estimates of future cash flows and risk premia in the accounting figures (for example, Borio and Tsatsaronis, 2004; Goodhart, 2004; Adrian and Shin, 2008). Other obvious examples with a potential first-order effect on procyclicality include the characteristics of deposit insurance schemes, of resolution procedures, and of the monetary policy regime in place.[50]

Second, within prudential arrangements, while a lot of attention has been devoted to capital requirements, several other possibilities are also worth considering. As a preliminary step, prudential filters can be applied to accounting figures to offset undesirable features, such as loan provisioning rules that are not sufficiently forward-

49. To some extent, these arrangements are already in place in a number of jurisdictions (see Borio, 2009).

50. By comparison with prefunded deposit insurance, unfunded (survivor pays) insurance schemes increase procyclicality in the face of systemwide strains by requiring payments precisely when capital is more scarce for institutions. See Kashyap, Rajan, and Stein (2008) for a proposal to set up systemic insurance schemes activated by aggregate losses in the system. The same can be true of resolution procedures that are not conditional on the degree of stress in the financial system as a whole. Finally, monetary policy frameworks that focus narrowly on the pursuit of price stability over short horizons may unwittingly accommodate the build-up of financial imbalances if these take place when inflation remains low and stable (Borio and Lowe, 2002a; Borio and White, 2004; Borio, 2006).

looking and prudent (see below). Since the availability of funding liquidity is procyclical, funding liquidity standards that rely on quantitative minimum requirements that are invariant to the state of the economy risk exacerbating financial strains once they emerge, by acting as shock amplifiers rather than shock absorbers.[51] Increasing variation margins when volatility spikes can have a similar effect (CGFS, 1999; Borio, 2003b). High minimum loan-to-value ratios can add to procyclicality by increasing the sensitivity of the supply of credit to the assets used as collateral (Borio, Furfine, and Lowe, 2001). Arrangements could therefore be adjusted in all of these areas.

Third, at the same time, capital standards remain a key potential area for adjustment, given their central role and far-reaching effects. The spectrum of options for regulatory capital ranges from reducing its cyclical risk sensitivity to deliberately introducing elements of countercyclicality within the existing framework. There are various ways to accomplish this (Gordy and Howells, 2006). Examples include strengthening the through-the-cycle orientation of minimum capital requirements; setting the corresponding risk parameters based on smoothed outputs of financial institutions' internal risk models; and adding a countercyclical adjustment to the minima based on measures of the financial cycle (a form of macroprudential overlay). The adjustments could be hardwired to the minima (Pillar 1 in Basel II) or encouraged through the supervisory review process (Pillar 2).

Fourth, there are a number of areas in which automatic stabilizers could be considered. In the area of collateral requirements, possibilities include seeking to implement through-the-cycle margining requirements (Geithner, 2006) and enforcing minimum loan-to-value ratios that are comparatively low and/or based on valuations that are less sensitive to market prices. Similarly, supervisors may consider that accounting standards do not allow for sufficiently forward-looking or prudent provisions, such as not permitting through-the-cycle provisions for loans (sometimes known as dynamic provisions) based on average historical experience, in

51. For a discussion of liquidity standards that take a systemwide perspective into account, see Borio (2003b) and Morris and Shin (2008). Note that while Morris and Shin talk about putting in place liquidity requirements they presumably mean liquidity buffers, since state or time (state) invariant liquidity requirements would act as amplifiers at times of stress. For a discussion of the interaction between market and funding liquidity, see Borio (2003b), for its theoretical modeling, Brunnermeier and Pedersen (2007), and, for a survey, Shim and von Peter (2007).

place until recently in Spain (Fernández de Lis, Martínez Pagés, and Saurina, 2001). In that case, they can add the difference between what they find appropriate and the accounting figures to minimum capital requirements.[52] Importantly, adjustments to capital standards within the existing framework could be made based on specific rules rather than discretion. A possibility worth examining would be to index the macroprudential overlay to some measure of the financial cycle. For example, one could tie capital standards inversely to measures of risk premia or indicators of market perceptions of financial institutions' strength, exploiting their thermometer characteristics. Alternatively, one could tie them positively to aggregate credit growth or asset prices relative to trend, exploiting their barometer features.

Finally, regardless of the specifics, for arrangements to be successful they will need to constrain the room for regulatory arbitrage, both across countries and between the regulated and unregulated sectors. Across countries, this raises thorny issues of coordination between home and host authorities.[53] The harder challenge, however, is how to constrain behavior outside the regulated sector. To the extent that an indirect approach based on restrictions on the regulated institutions proved insufficient, the extension of the coverage of prudential instruments would need to be considered.

3.2.3 Institutional setup

Two key issues that need to be addressed in the institutional setup for the implementation of the framework are the needs to ensure accountability and to align objectives with the available know-how. Accountability calls for a clear mandate, transparency, and effective processes to hold policymakers responsible. Accountability

52. Admittedly, this is less effective than directly adjusting accounting standards. Even if publicly disclosed, such prudential provisions may be less effective in reducing procyclicality than if dynamic provisions were allowed for accounting purposes: since they are not charged against current income, prudential provisions forgo the disciplinary effect that operates through the market's focus on earnings (the bottom line). Even so, they can help constrain dividend payments during expansions, thereby increasing the size of the capital buffers, and they release buffers when losses materialize and accounting provisions spike.

53. Financial and real conditions may and do differ across countries. For institutions with international operations, this would suggest calibrating instruments with respect to their individual consolidated exposures to the corresponding country's conditions rather than in terms of the nationality or residence of the firm. These exposures could derive from cross-border lending or direct operations in host countries.

is especially important for disciplining any reliance on discretion that complements automatic stabilizers. It can generally be enhanced by making sure that the measures used are as simple and transparent as possible. One could imagine a setup similar to the one now being employed for monetary policy. At the same time, given the lags involved and the inevitable "fuzziness" in definition and measurement, it would be unrealistic to expect that an equivalent degree of accountability and transparency is feasible.

Addressing the imperfect alignment of goals, instruments, and know-how in the institutional setup is a difficult and controversial task. At a minimum, a financial stability framework with a macroprudential orientation requires close cooperation between a broad range of authorities with respect to both its development and implementation. The close bearing on financial stability of a wide range of policies, under the responsibility of authorities with very different perspectives, requires this.

At the same time, a key ingredient of success is to leverage the comparative advantage of the various authorities involved. This is especially important for monetary and prudential authorities. Monetary authorities have an edge in understanding the nexus between the macroeconomy, the financial system, and the functioning of financial markets. Prudential authorities have an edge in understanding the risk management practices of the regulated institutions. For instance, one could set up special committees involving these types of authority charged with implementing those macroprudential overlays in regulatory and supervisory tools executed on a discretionary basis.

4. Conclusion

The measurement of financial (in)stability is fundamentally fuzzy. This reflects a number of factors, including a lack of consensus on the most appropriate analytical framework, the infrequent incidence of episodes of financial distress, and limitations in the available measurement tools. These tools are very poor at capturing the feedback effects that are at the heart of financial instability and that operate both within the financial system and between the financial system and the real economy. At their best, they can provide indications of the general buildup in risks. As a result, there is always a danger that policymakers may be lulled into a false sense of security.

No doubt these shortcomings are serious: there is a urgent need for further analytical and empirical work to address them. We have suggested what the most promising directions might be. But notwithstanding them, there is still ample scope for progress in establishing a more effective operational framework for financial stability as long as these shortcomings are fully taken into account.

We have argued that progress can be made in several ways: by strengthening the macroprudential orientation of financial regulation and supervision; by addressing the procyclicality of the financial system more systematically; by relying as far as possible on automatic stabilizers, rather than discretion, while disciplining the use of any such discretion; and by setting up institutional arrangements that leverage the comparative expertise of the various authorities involved in safeguarding financial stability, not least financial supervisors and central banks. The global credit crisis that has engulfed financial systems since the summer of 2007 provides a unique opportunity for steps in this direction.

Appendix
Endogenous Cycles and EWIs

This appendix is a first, preliminary attempt to update and extend the EWIs developed by Borio and Lowe (2002a, 2002b, 2004) and to assess how they would have fared prior to the current crisis.[54] It refines the previous indicators by introducing property prices alongside equity prices.

As discussed in the main text, Borio and Lowe's approach is grounded in the endogenous cycle view of financial instability. They argue that the coexistence of unusually rapid credit growth and asset price increases indicates the buildup of financial imbalances that raise the likelihood of subsequent financial distress. They develop EWIs drawing on a large set of industrial and emerging market countries. Their proxy for misaligned asset prices is an asset price gap, measured by the deviation of inflation-adjusted (real) equity prices from their long-term trend; and that for credit booms is a credit gap (measured by deviations of the ratio of private sector credit to GDP from its trend). The trends are calculated on the basis of one-sided Hodrick-Prescott filters. Borio and Lowe assess various combinations and thresholds and find that for industrial countries, the EWI has the best performance in terms of low noise-to-signal ratio as well as the percentage of crises predicted when a warning signal is issued if the credit gap exceeds 4 percentage points and the equity price gap is greater than 40 percent.[55] Flexible horizons are incorporated by analyzing forecast intervals that vary in length, from one to three years ahead.[56]

One drawback of that analysis, as already pointed out at the time, is that property prices were not included in the indicator. With the benefit of a few more observations, we extend the analysis to include

54. See Borio and Drehmann (2009) for a more detailed discussion of the issues raised in the appendix.

55. The noise-to-signal ratio is the ratio of the fraction of type II errors (that is, the number of false positive signals issued relative to noncrisis periods) over one minus the fraction of type I errors (that is, the number of instances in which no signal was issued relative to the number of crises observed). Several studies minimize the noise-to-signal ratio and thereby weigh both types of error equally (for example, Kaminsky and Reinhart, 1999). Borio and Lowe argue that equal weighting is not appropriate for practical policy purposes, and they apply judgment to derive what constitutes the best threshold, giving more weight to type I errors.

56. They assume that the signal is correct if a crisis occurs in any of the years included in the horizon. For example, for a three-year horizon, a correct signal is given if the credit gap and the equity gap jointly exceed their corresponding thresholds least in one of the three years prior to a crisis.

them. This is critical to make proper inferences in the current episode, where the lag between the peak in equity and property prices has been considerably longer than in previous episodes (Borio and McGuire, 2004). The exercise is carried out for 18 industrial countries.[57]

We construct a credit gap, an equity gap and a property price gap. The property price gap combines both residential and commercial property prices, with weights that are rough estimates of their shares in private sector wealth. We then assess the performance of the EWI in terms of the percent of crises predicted and the noise-to-signal ratio for different thresholds, estimating the best indicators through a grid search. We carry out the analysis in sample (up to 2003) and then forecast out of sample, over the remaining years, ending in 2007, the last full year for which we have data, and in 2008 for the information concerning the crises. Table A1 summarizes the results.

In sample, we find that the best performance is achieved if the credit gap exceeds 6 percent and at the same time either the equity gap exceeds 60 percent or the property gap exceeds a threshold that ranges from 15 to 25 percent. Especially for horizons of up to two years, a threshold of 15 percent is relatively attractive, as it predicts a high proportion of crises (about 70 percent), although it produces a higher percentage of false alarms. For a horizon of up to three years, a higher threshold is preferable, as financial distress does eventually emerge and the noise-to-signal ratio is lower. As expected, the predictive power increases and the noise-to-signal ratio decreases as the horizon is lengthened, confirming that the timing of the reversal of the financial imbalance is very hard to predict. Comparing the different thresholds, it is apparent that a higher threshold implies lower predictive power, but also a lower noise-to-signal ratio.

How do the indicators perform in the more recent period? As an illustration, figure A1 plots the credit and property gaps for the Unites States, the epicenter of the crisis. We do not plot the equity

57. The countries included in the sample are Australia, Belgium, Canada, Denmark, Finland, France, Germany, Ireland, Italy, Japan, the Netherlands, New Zealand, Norway, Spain, Sweden, Switzerland, the United Kingdom, and the United States. We use annual data. Our sample size is restricted by the property price indexes, which combines retail and commercial property indexes and which for most countries are available only from 1970 onward. All gaps are measured as percentage deviations from a one-sided Hodrick-Prescott trend (with lambda = 1,600), which only uses information that is available at the point in time the prediction is made. A gap is only calculated if at least ten years of data are available. Therefore, the sample used for the calibration of the thresholds is from 1980 to 2003. In this period, 13 crises occurred. The timing of crisis is based on Borio and Lowe (2002a) and extended based on Laeven and Valencia (2008).

Table A1. In- and Out-of-Sample Performance of Early Warning Indicators[a]

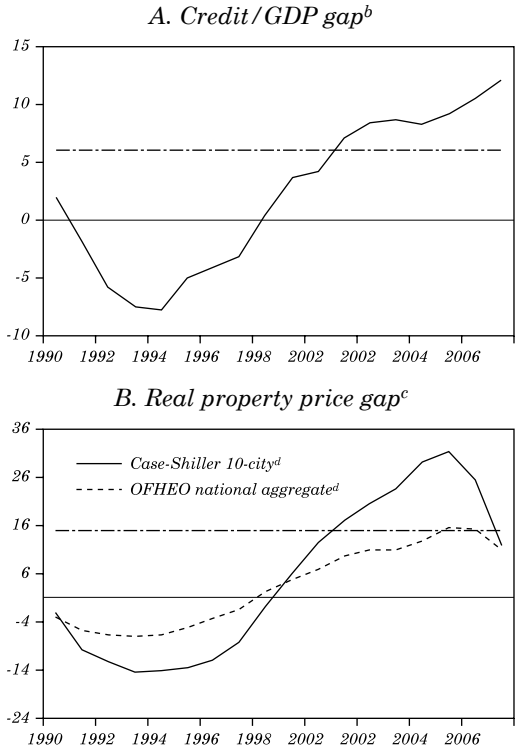
	In-sample		*Out-of-sample*			
			(Definition 1)		*(Definition 2)*	
Threshold and horizon	*% crises predicted*	*Noise/signal*	*% crises predicted*	*Noise/signal*	*% crises predicted*	*Noise/signal*
Credit gap > 6% and either property gap > 15% or equity gap > 60%						
1	46	0.23	67	0.53	50	0.65
2	69	0.13	67	0.53	50	0.69
3	69	0.11	67	0.53	64	0.52
Credit gap > 6% and either property gap > 20% or equity gap > 60%						
1	31	0.21	33	0.53	21	0.82
2	54	0.11	33	0.50	29	0.97
3	69	0.07	33	0.47	36	0.70
Credit gap > 6% and either property gap > 25% or equity gap > 60%						
1	31	0.18	33	0.24	7	1.40
2	46	0.11	33	0.19	7	1.62
3	62	0.06	33	0.13	7	2.33

Source: Authors' calculations.

a. A gap is measured as percentage points from an ex ante, recursively calculated Hodrick-Prescott trend (lambda = 1,600). Thresholds are given in percent. A signal is correct if a crisis takes place in any one of the years included in the horizon ahead.

price gap, since it was exceeded at the time of the dot-com boom, but subsequently turned negative.

Figure A1. Estimated Gaps for the United States[a]



Source: BIS calculations.
a. Gaps are estimated using a rolling Hodrick-Prescott filter with lambda set to 1,600. The horizontal dashed lines refer to the threshold values that define the existence of a boom: 6 percent for credit/GDP gap; 15 percent for real property price gap.
b. In percentage points.
c. Refers to the residential property price component.
d. In percent; refers to combined residential and commercial property prices.

The figure suggests that the indicator would have picked up the vulnerabilities. Taken at face value, signs of vulnerabilities began to emerge as far back as 2001, as both the credit gap and the property price gap started to exceed the critical threshold jointly, at least if the residential component of the property price index is measured by the Case-Shiller ten-city index. If the less variable Office of Federal

Housing Enterprise Oversight (OFHEO) index is used, the threshold is reached only in 2005.[58]

A more formal out-of-sample exercise covering all the industrial countries for which data are available is harder to perform at this early stage, in the midst of the turmoil. At least two problems emerge. First, given that the flexible horizon extends up to three years, we can only fully assess the predictive content of the signals issued in 2004; for subsequent ones the full horizon has not yet materialized. Second, and more importantly, defining which country is in distress is not unambiguous. This highlights some of the issues raised in assessing financial instability, especially in real time.

To address the ambiguity in the identification of the crisis, we adopt two definitions, going from the more to the less restrictive:[59]

—Definition 1: Countries where more than one large bank failed or had to be supported by the government in an emergency operation;[60]

—Definition 2: Countries that undertook at least one of the following policy operations: extend deposit insurance guarantees beyond the household sector, buy assets, or undertake capital injections.[61]

58. The gap based on property prices using the Case-Shiller aggregate index is in between the other two and breaches the critical threshold in 2003. The in-sample estimates presented in table A1 are unaffected by the choice of the property price measure for the United States.

59. The cut-off date for this analysis was 20 October 2008, and depending on future developments, the classifications of which country is in turmoil may change. For simplicity, we assume that crises start in 2007, even though most policy measures were adopted in 2008. We also used the alternative assumption that all crises started in 2008. In this case, one problem is that for four countries (Belgium, Canada, Denmark, and the United Kingdom), residential and/or commercial property prices are not available for 2007, so that the property gap cannot be fully estimated. Based on judgmental estimates, we found comparable results, except that the crisis in Belgium can also be successfully predicted. For exploratory reasons, we used two additional crisis definitions. Definition 2(a) is similar to definition 2 except that it identifies a crisis if countries adopted at least two of the policy measures; the results are very similar to those for definition 2. Definition 2(b) is the least restrictive, as it includes any of the policy measures listed in definition 2, as well as an expansion of the coverage of deposit insurance for retail deposits. As all countries except for Japan have implemented at least one of these policies, the noise-to-signal ratio drops to zero since our EWI correctly predicts that Japan is not a crisis country.

60. The countries that are in a crisis according to this definition are the United States, the United Kingdom, and Belgium.

61. We take account of policy actions which have been announced but may not yet be fully implemented. The countries that are in a crisis according to this definition are Australia, Belgium, Canada, France, Germany, Ireland, Italy, the Netherlands, Norway, Spain, Sweden, Switzerland, the United Kingdom, and the United States.

Based on definition 1, only three countries have faced a crisis, namely, the United States, the United Kingdom, and Belgium. Based on definition 2, fourteen of the eighteen countries have faced distress.

On balance, the performance of the indicator is encouraging, although far from perfect and a function of the definition used. The variant of the indicator based on the lowest threshold for property prices (15 percent) performs best, while the others fail to pick a significant number of cases. moreover, while the noise-of-signal ratio increases considerably compared with the in-sample estimates, a look behind the aggregate numbers is quite revealing. With definition 1, the indicator picks two out of three cases independent of the forecast horizon; the one missed is Belgium. With definition 2, the three-year indicator picks nine out of the fourteen crises; those missed are Belgium, Canada, Germany, the Netherlands, and Switzerland. At the same time, only two false positive signals are issued, for Denmark and New Zealand.

The results suggest a number of observations. First, while the indicator does identify distress in the country that has been at the epicenter of the crisis such as the United States, it fails to pick the international transmission of the problems. In particular, it does not capture those cases in which banks have run into trouble as a result of losses on their international exposures in the absence of signs of financial imbalances in the domestic economy, most notably in Germany and Switzerland.[62] This is no surprise, since by construction the indicator assumes that banks in any given country are exposed only to the financial cycle in that country. Obviously, this is an aspect that calls for improvement and has implications for the calibration of prudential arrangements (see the main text). Second, the countries for which the indicator issues false positive signals include two that have exhibited sizable booms and one institution has already failed in at least one of them (Denmark). We may need to wait longer to see exactly how the indicator performs.

A broader issue is also apparent. Which definition of distress is more appropriate? Definition 1 excludes preventive policies designed to deal with the threat of imminent distress, whereas

62. Canada and the Netherlands exceed the threshold in terms of either credit growth or property prices, but not both. In Belgium, the property price gap in 2006 was 14.45, just below the threshold. Furthermore, in 2007, the credit gap was above 10. Even though data are only available until mid-2007, they suggest that the property price gap in this year would also have been greater than 15.

definition 2 includes them. Conceptually, definition 2 is arguably more appropriate. We take the view that the extraordinary measures included in the definition are forms of crisis management, rather than prevention: the system should be capable of being stable without them. At the same time, this ambiguity does highlight the grey area that exists when the authorities try to intervene quite early in the game, before more obvious signs of insolvency are apparent. These ambiguities are compounded when actions are taken partly to address the spillover effects of policies taken in other countries. The extension of guarantees to prevent a drain of funding in the domestic market is an obvious example. Would distress fail to materialize without them? This type of policy contagion is quite novel in recent experience and reflects the global nature of the crisis when several highly interdependent financial systems are facing incipient strains simultaneously.

Overall, we conclude that the recent credit crisis confirms the usefulness of the family of indicators rooted on the endogenous cycle view of financial instability. At the same time, it also highlights some of their limitations and the potential scope for improvement.

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Measuring and Managing Macrofinancial Risk and Financial Stability: A New Framework

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The vulnerability of a national economy to volatility in the global markets for credit, currencies, commodities, and other assets has become a central concern of policymakers. The responsibility for managing these risks at the national level is often given to the central bank. However, the conventional models and analytical tools used by central banks today are ill suited for analyzing these types of risk. This paper proposes a new approach to improve the way central banks can analyze and manage the financial risks of a national economy. It is based on the modern theory and practice of Contingent Claims Analysis (CCA), which is successfully used today at the level of individual banks by managers, investors, and regulators. When applied to the analysis and measurement of credit risk, CCA is commonly called the Merton Model.[1] The basic analytical tool is the risk-adjusted balance sheet, which shows the sensitivity of the enterprise's assets and liabilities to external shocks. At the national level, the sectors of an economy are viewed as interconnected portfolios of assets, liabilities, and guarantees—some explicit and others implicit. Traditional approaches

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1. See Merton (1973, 1974, 1977, 1992, 1998). Initially developed for valuation of corporate firms, CCA has been adapted to financial institutions and sovereigns.

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have difficulty analyzing how risks can accumulate gradually and then suddenly erupt in a full-blown crisis. The CCA approach is well-suited to capturing such nonlinearities and quantifying the effects of asset-liability mismatches within and across institutions. Risk-adjusted CCA balance sheets facilitate simulations and stress testing to evaluate the potential impact of policies to manage systemic risk.

The paper starts with a description of contingent claims analysis and then outlines a simple framework of CCA balance sheets for four key sectors (namely, the sovereign, financial, corporate, and household sectors). It describes how the sectoral CCA balance sheets can be constructed and linked together. Several different types of risk exposures and risk transmission channels are discussed. Finally, the paper shows how the CCA financial risk indicators can be used in stress testing, linked to macroeconomic and monetary policy model.

1. Contingent Claims Analysis

A contingent claim is any financial asset whose future payoff depends on the value of another asset. The prototypical contingent claim is an option—the right to buy or sell the underlying asset at a specified exercise price by a certain expiration date. A call is an option to buy; a put is an option to sell. Contingent claims analysis is a generalization of the option pricing theory pioneered by Black and Scholes (1973) and Merton (1973). Since 1973, option pricing methodology has been applied to a wide variety of contingent claims. In this paper we focus on its application to the analysis of credit risk and guarantees against the risk of default.

The contingent claims approach is based on three principles: the values of liabilities are derived from assets; liabilities have different priority (that is, senior and junior claims); and, assets follow a stochastic process. The liabilities consist of senior claims (such as senior debt), subordinated claims (such as subordinated debt), and junior claims (equity or the most junior claim). As total assets decline, the value of risky debt declines and credit spreads on risky debt rise.

Balance sheet risk is the key to understanding credit risk and crisis probabilities. Default happens when assets cannot service debt payments. Uncertain changes in future asset value, relative to promised payments on debt, is the driver of default risk. Figure 1 illustrates the key relationships. The uncertainty in asset value is represented by a probability distribution at time horizon T. At the end of the period, the value of assets may be above the promised

payments, indicating that debt service can be made, or below the promised payments, leading to default. The area below the distribution in panel A of figure 1 is the "actual" probability of default. The asset-return probability distribution used to value contingent claims is not the "actual" one but the "risk-adjusted" or "risk-neutral" probability distribution, which substitutes the risk-free interest rate for the actual expected return in the distribution. This risk-neutral distribution is the dashed line in panel B, with expected rate of return r, the risk-free rate. Thus, the risk-adjusted probability of default calculated using the risk-neutral distribution is larger than the actual probability of default for all assets that have an actual expected return (μ) greater than the risk-free rate r (that is, a positive risk premium).[2]

The calculations of the actual probability of default is outside the CCA/Merton Model, but it can be combined with an equilibrium model of underlying asset expected returns to produce estimates that are consistent for expected returns on all derivatives, conditional on the expected return on the asset. The reason is that one does not have to know expected returns to use the CCA/Merton Models for the purpose of value or risk calculations.

The value of assets at time t is $A(t)$. The asset return process is $dA/A = \mu_A dt + \sigma_A \varepsilon \sqrt{t}$, where μ_A is the drift rate or asset return, σ_A is equal to the standard deviation of the asset return, and ε is normally distributed, with zero mean and unit variance. The probability distribution at time T is shown in panel A of figure 1.

Default occurs when assets fall to or below the promised payments, B_t. The probability of default is the probability that $A_t \leq B_t$ which is

$$\begin{aligned}\text{Prob}(A_t \leq B_t) &= \text{Prob}\left\{A_0 \exp\left[(\mu_A - \sigma_A^2/2)t + \sigma_A \varepsilon \sqrt{t}\right] \leq B_t\right\} \\ &= \text{Prob}(\varepsilon \leq -d_{2,\mu}).\end{aligned}$$

Since $\varepsilon \sim N(0,1)$, the actual probability of default is $N(-d_{2,\mu})$, where

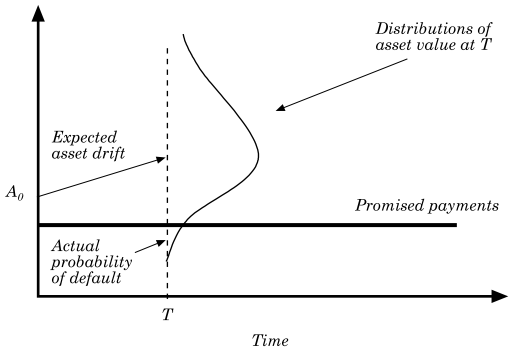
$$d_{2,\mu} = \frac{\ln(A_0/B_t) + (\mu_A - \sigma_A^2/2)t}{\sigma_A \sqrt{t}}.$$

$N(\bullet)$ is the cumulative standard normal distribution.

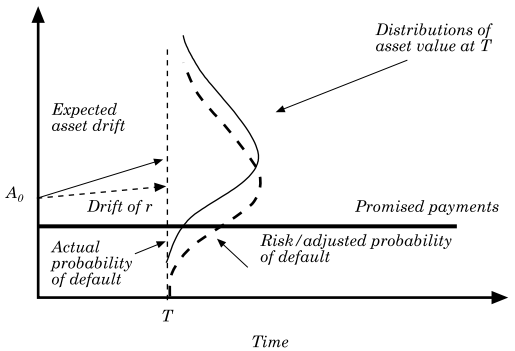
2. See Merton (1992, pp. 334–43, 448–50).

Figure 1. Asset Value and Probability of Default

A. Asset value



B. Asset value and actual and risk-adjusted probability of default



Source: Authors' elaboration; adapted from Gray and Malone (2008).

Shown in panel B of figure 1 is the probability distribution (dashed line) with drift of the risk-free interest rate, r. The risk-adjusted probability of default is $N(-d_2)$, where

$$d_2 = \frac{\ln(A_0/B_t) + (r - \sigma_A^2/2)t}{\sigma_A\sqrt{t}}.$$

Box 1 presents the Merton Model equations. (See the appendix for more details, including extensions of the Merton Model.)

Box 1. Merton Model Equations for Pricing Contingent Claims

The total market value of assets at any time, t, is equal to the market value of the claims on the assets, equity, and risky debt maturing at time T:

$$Assets = Equity + Risky\ Debt,$$

$$A(t) = J(t) + D(t).$$

Asset value is stochastic and in the future may decline below the point at which debt payments cannot be made on scheduled dates. The equity can be modeled and calculated as an implicit call option on the assets, with an exercise price equal to the promised payments, B, maturing in $T - t$ periods. The risky debt is equivalent in value to default-free debt minus a guarantee against default. This guarantee can be calculated as the value of a put on the assets with an exercise price equal to B:

$$Risky\ Debt = Default\text{-}Free\ Debt - Debt\ Guarantee,$$

$$D(t) = Be^{-r(T-t)} - P(t).$$

We omit the time subscript at $t = 0$.

The value of the equity is computed using the Black-Scholes-Merton formula for the value of a call:

$$J = AN(d_1) - Be^{-rT}N(d_2)$$

and

$$d_1 = \frac{\ln\left(\frac{A}{B}\right) + \left(r + \frac{\sigma_A^2}{2}\right)T}{\sigma_A\sqrt{T}} \quad and \quad d_2 = d_1 - \sigma_A\sqrt{T},$$

where r is the risk-free rate, σ_A is the asset return volatility, and $N(d)$ is the cumulative probability of the standard normal density function below d.

The formula for the delta of the put option is $N(d_1) - 1$. The yield to maturity on the risky debt, y, is defined by

$$y = \frac{\ln(B/D)}{T},$$

where $D = Be^{-yT}$ and the credit spread is $s = y - r$.
The risk-neutral or risk-adjusted default probability is $N(d_2)$.

Example: Assuming that $A = \$100$, $\sigma_A = 0.40$ (40 percent), $B = \$75$, $r = 0.05$ (5%), and $T = 1$ (one year), the value of the equity is \$32.37, the value of risky debt is \$67.63; the yield to maturity on the risky debt is 10.34 percent, and the credit spread 5.34 percent. The risk adjusted probability of default is 26 percent.

Financial fragility is intimately related to probability of default. Shocks to flows, prices, or liquidity frequently end up being converted into credit risk in a crisis. Default is hard to handle in traditional macroeconomic models, in part because the assumptions usually exclude the possibility of default. In addition, flow-of-funds accounts and accounting balance sheets cannot provide measures of risk exposure that are forward-looking estimates of losses. CCA is a framework that explicitly includes the probability of default.

2. Contingent Claim Balance Sheets for Sectors

We view an economy as a set of interrelated balance sheets with four types of aggregate sectors—corporate, financial, household, and sovereign. The same general principles of contingent claims that apply to the analysis of a single firm can also be applied to an aggregation of firms. The liabilities of a firm, a portfolio of firms in a sector, or the sovereign (that is, the combined government and monetary authorities) can be valued as contingent claims on the assets of the respective firm or sector or sovereign. The corporate sector refers to an aggregation of all nonfinancial firms. Treating the corporate sector as one large firm and the financial sector as one large institution is a very simplified way of looking at the balance sheet, but we start out with this stylized framework to illustrate the risk characteristics of the sector for the purposes of this analysis. Later in the paper, we look at the major financial institutions separately and group the corporate firms into subsectors. The key elements of the balance sheets for the corporate, financial, household, and sovereign sectors are shown in table 1.

2.1 Economywide Macroeconomic Contingent Claim Balance Sheets and Risk Exposures

Building on the theory of contingent claims laid out above, the macrofinance valuation identities use put-call parity relationships, which state that the asset value A of each sector is equal to the value of its equity plus the value of its risky debt.[3] The four primary sectors

3. See Gray, Merton, and Bodie (2002) and Gapen and others (2004).

Table 1. Balance Sheets for the Corporate, Financial, Household, and Sovereign Sectors

Sector	*Assets*	*Liabilities*
Corporate	Corporate assets	Debt; equity
Financial	Loans and other assets (including loans to corporations, households, and the sovereign); financial guarantees	Debt and deposits; equity
Household	Household assets (including household income and savings in the form of deposits and other financial assets); Net worth in household real estate assets (on subsidiary balance sheet, which includes mortgage debt)	Household net worth (claim on household assets); consumption is a dividend payment out of assets associated with this claim
Sovereign (government and monetary authorities	Foreign currency reserves; net fiscal asset (present value of taxes minus expenditures); other public assets	Financial guarantees; foreign currency debt; base money; local currency debt

Source: Authors' elaboration.

of the economy, for the corporate, financial, sovereign, and household balance sheets, are complemented by the foreign sector. The CCA balance sheet equations for each sector j have the sector assets equal to equity (that is, junior claims) plus risky debt. The function E_j refers to the period t value of sector j's equity (that is, the junior claim), which is modeled as an implicit call option. The horizon period is T for the calculation of the implicit option values. Risky debt, D_j, is equal to the default-free value of the debt, denoted by $\bar{B}_i$ ($\bar{B}_i \equiv B_i e^{-rT}$), minus the value of the implicit put option, which is denoted by P_j (the expected losses associated with the debt). The time horizon T is the same for all sectors for the calculation of the CCA values at each point in time. Using the notation above, the following equations state the put-call-parity relationships for the four domestic sectors. For the corporate sector (C), assets, A_C, equal equity, E_C, plus the risky debt, $\bar{B}_C - P_C$:

$$A_C = E_C + (\bar{B}_C - P_C).$$

For the financial sector (F), assets, A_F, plus contingent financial support from the sovereign, αP_F, equals equity, E_F, plus the value of risky debt/deposits, $\bar{B}_F - (1-\alpha)P_F$:

$$A_F + \alpha P_F = E_F + \left[\bar{B}_F - (1-\alpha)P_F\right],$$

where P_F is the implicit put option to the financial sector.[4] The model assumes that the government's contingent liability, or the value of the explicit or implicit sovereign guarantee, is a fraction α of the total P_F, and the remainder, $(1-\alpha)P_F$, is credit risk remaining in the debt and deposits of the financial sector.

For the sovereign, the assets of the sovereign, A_S, include foreign currency reserves, R_{MA}; the net fiscal asset, A_G (defined as the present value of taxes and revenues, including seigniorage, minus the present value of government expenditures); and other public assets, A_{Other}. The liabilities of the sovereign include base money, M_{BM}, risky local currency debt $(\bar{B}_{SLC} - P_{SLC})$, risky foreign currency debt $(\bar{B}_{SFX} - P_{SFX})$, and financial guarantees/contingent liabilities, αP_F:

$$A_S = R_{MA} + A_G + A_{Other} = M_{BM} + (\bar{B}_{SLC} - P_{SLC}) + (\bar{B}_{SFX} - P_{SFX}) + \alpha P_F.$$

For the household sector, the household asset, A_H, is the sum of the household sector's financial wealth, A_{FIN}, the present value of its labor income, A_L, and equity in real estate, $E_{H,RE}$. The debt of households to banks and nonbanks is frequently tied to homes and real estate. It is therefore practical to have two segregated but linked household CCA balance sheets. The subsidiary balance sheet would have real estate as the primary asset, with related debt on the liability side.[5] The households' equity in real estate is modeled as real estate assets, $A_{H,RE}$, minus risky household mortgage related debt, $\bar{B}_{H,RE} - P_{H,RE}$:

$$\begin{aligned} A_H &= A_{FIN} + A_L + E_{H,RE} \\ &= A_{FIN} + A_L + \left[A_{H,RE} - (\bar{B}_{H,RE} - P_{H,RE})\right] \\ &= E_H + c_H. \end{aligned}$$

The household sector asset, A_H, is equal to the household net worth, E_H, plus c_H which is consumption modeled as a dividend payment out of the household asset up to time T.

4. Merton (1977) was the first to demonstrate that the government's guarantee to banks could be modeled as an implicit put option.

5. This structure has many variations. Debt could be included on the main household balance sheet, or additional subsidiary balance sheets could be included relating specific debt obligations to related assets.

The four-sector CCA balance sheets can be integrated into an economywide balance sheet, as shown in table 2. For each sector, the assets, plus contingent assets (or minus contingent liabilities), minus equity and junior claims, and minus risky debt sum to zero (down the column in table 2). These interlinked economic balance sheets demonstrate the interdependence among sectors, with one sector long a certain implicit option (plus sign) and another sector short the same implicit option (minus sign). For example, the economic balance sheet of the banking sector has assets consisting of corporate loans (default-free debt minus the value of a put option). The banking sector also includes contingent liabilities (implicit put options) from the government as an asset, which is an obligation (short put option) on the government's economic balance sheet.[6]

Table 2. Economywide Contingent Claim Balance Sheet with Risk Exposures across Sectors (Implicit Put and Call Options)

	Corporate	*Households*	*Financial*	*Sovereign*	*Foreign*
Assets	A_C	$A_{FIN}+A_L$ $+[A_{H,RE}$ $-(\overline{B}_{H,RE}$ $-P_{H,RE})]$	A_F	$R_{MA}+A_G$ $+A_{Other}$	
Contingent assets and liabilities			$+\alpha P_F$	$-\alpha P_F$	
Equity/junior and subordinate claims	$-E_C$	$-E_H-c_D$	$-E_F$	$-M_{BM}-\overline{B}_{SLC}$ $+P_{SLC}$	Foreign claims
Barrier	$-\overline{B}_C$		$-\overline{B}_F$	$-\overline{B}_{SFX}$	
Expected loss (put)	$+P_C$		$+(1-\alpha_G)P_F$	$+P_{SFX}$	
Sum	0	0	0	0	0

Source: Authors' elaboration.

The financial assets of the sectors can be separated into claims on foreigners and claims on domestic entities. For simplicity, the detailed cross-holdings by the household sector, financial sector, and foreign sector on the other sectors are not shown in table 2.

6. Macrofinancial risk models similar to this framework have been calibrated for over 20 countries (although only a few incorporate the household sector).

2.2 Interrelationship of Macrofinancial Contingent Claim Balance Sheets, Risk Exposures, and Traditional Macroeconomic Flows

We now show how the traditional macroeconomic flow-of-funds account can be recovered from the CCA equations when risk goes to zero. When the volatility of assets in the CCA balance sheet equations (table 2) is set to zero, the values of the implicit put options go to zero.[7] The result is the accounting balance sheet of the sectors. The flow of funds can thus be seen as a special deterministic case of the CCA balance sheet equations when volatility is set to zero and annual changes are calculated. The implicit put options in risky debt and contingent liabilities allow for risk to be transmitted between sectors in the CCA model. Without volatility, the risk transmission between sectors is lost.

The combined accounts—that is, income/flow, mark-to-market balance sheets, and risk exposure measures—comprise the three important sets of interrelated accounts in the economy, which are somewhat similar to the accounts in large modern financial institutions.[8] Risk managers would find it difficult to analyze the risk exposure of their firm or financial institution by relying solely on the income and cash flow statements, without taking into account (mark-to-market) balance sheets or information on their institution's derivative or option positions. Country risk analysis that relies only on a macroeconomic flow-based approach is deficient in a similar way, given that the traditional analysis does not take into account the volatility of assets.

2.3 Measuring Implied Asset Value and Volatilities Using Market Prices

The market value of the assets of corporations, financial institutions, or sovereigns cannot be observed directly. However, the observed prices and volatilities of market-traded securities can be

7. If the volatility of assets goes to zero, then in the put option formula $N(-d_1) = N(-d_2) = 0$, which means that the implicit put option values in the sectors go to zero. It is not possible to measure the expected loss and credit risk with asset volatility set to zero. Furthermore, if volatility goes to zero, then $N(-d_1) = N(-d_2) = 1$, and the value for the junior claim of the representative sector then reduces to the accounting net worth, equal to deterministic assets minus a measure of the book value of debt. See Gray and Malone (2008) for details.

8. Enterprise risk management is a framework to comprehensively measure and manage risk in firms and financial institutions. Its use has expanded in recent years.

used to estimate the implied values and volatilities of the underlying assets.[9] These implied asset values and asset volatilities can be used to calibrate the pricing and risk model of major sectors in the economy. We discuss briefly how this can be done first for firms and financial institutions, then for the sovereign.

2.3.1 Firms and financial institutions

Domestic equity markets provide pricing and volatility information for the calculation of implied assets and implied asset volatility in corporations and bank and nonbank financial institutions. The simplest method solves two equations for two unknowns, asset value and asset volatility. Details are shown in the appendix and in Merton (1974) and Crouhy, Galai, and Mark (2000). Moody's KMV has successfully applied its version of the CCA model to measure the implied asset values and volatilities and to calculate expected default frequencies (EDFs) for over 50,000 firms and financial institutions in 55 countries around the world (Crosbie, 1999 and 2001).

For unlisted corporates and banks, the relationship between the accounting information and the risk indicators of companies with traded equity can be used as a guide for mapping the accounting information of companies without traded equity to default probabilities and risk indicators for institutions that do not have traded equity. An example is Moody's RiskCalc for corporate sectors in many countries and for banks in the United States.

2.3.2 Sovereign

Since the market value of sovereign assets cannot be observed directly, a similar calibration procedure can be used for the sovereign balance sheet to estimate implied sovereign assets and asset volatility. The prices in the international markets (including the foreign currency market), together with information from domestic market prices, provide the market information for the value and volatility of certain liabilities on the sovereign balance sheet.[10] If we subtract the financial guarantees from both sides of the sovereign balance sheet in the bottom rows in table 1, the remaining sovereign

9. An implied value refers to an estimate derived from other observed data. Techniques for using implied values are widely practiced in options pricing and financial engineering applications. See Bodie and Merton (2000).

10. See Gray, Merton, and Bodie (2002 and 2006).

liabilities are structured in a way that is consistent with the CCA framework. On the simplified sovereign balance sheet, the local currency debt of the government, held outside of the monetary authorities, and base money are *local currency liabilities,* which are modeled as a call option on the sovereign assets with the default barrier derived from the foreign currency debt. A simple two-claim CCA framework is used to calibrate the sovereign balance sheet by calculating implied sovereign assets, $V_{Sovereign}$, and asset volatility. This calibrated risk-adjusted balance sheet can be used to estimate credit risk in sovereign foreign currency and local currency debt, as well as other risk indicators. These indicators are robust measures of sovereign credit risk. [11] Scenarios and simulations can be carried out to evaluate the impact of fiscal and debt management policies and the impact of risk transfer onto the sovereign balance sheet.

2.3.3 Household sector balance sheet

Modeling household balance sheets using CCA principles is much more difficult than for firms, financial institutions, or sovereigns. Households have no traded equity, so techniques that use equity to imply assets are not applicable. One alternative for constructing the household balance sheet is to use a bottom-up approach. In the household sector, we can use macroeconomic data and information from household surveys to construct measures of the portfolio of household assets directly, for the most part, and try to estimate the volatility of household assets directly. Household balance sheet assets include financial assets (such as pension assets, annuities, mutual funds, and bank deposits) and estimated labor income (that is, the present value of expected labor income) (see Gray and Malone, 2008). For the household subsidiary balance sheet, direct estimation of the real estate prices, volatilities, and debt obligations is likely to be the most practical (but admittedly difficult) approach. Ideally. this analysis should be carried out not for the total household sector, but for households segmented by income groups.[12]

11. Applications to a wide range of countries are described in Gapen and others (2004, 2008) and Gray, Merton, and Bodie (2007). Extensions for modeling the valuation of sovereign local-currency debt are described in Gray and Malone (2008) and Gray and others (2008).

12. It may be very difficult to model households in this way due to data limitations in many countries. CCA balance sheets for households are therefore not as accurate as the corporate or bank or sovereign CCA balance sheet models.

2.4 Some Important Extensions and Refinements of CCA Models

Numerous extensions of the original Merton Model have been developed that relax certain assumptions in the original model. These extensions are described in more detail in the appendix, but two extensions are important to mention here.

First, recent research studies the relationship between the volatility skew implied by equity options and credit default swap (CDS) spreads. Hull, Nelken, and White (2004) establish a relationship between the implied volatility of two equity options, leverage, and implied asset volatility. This approach is, in fact, another way of implementing Merton's model to get spreads and risk-neutral default probabilities directly from the implied volatility of equity options. When the probability distributions derived from the option prices are negatively skewed (left tailed), then the implied underlying asset distribution is also negatively skewed, which results in a higher probability of assets being below the distress barrier and thus in higher spreads (Zou, 2003). In the sovereign CCA application, the probability distributions derived from foreign exchange option prices show that more negatively skewed foreign exchange distributions are associated with higher sovereign credit risk in emerging markets (see Gray, Merton, and Bodie, 2007). The CCA framework is thus able to link information from equity and foreign exchange options to credit risk and spreads. Financial stability reports usually look separately at credit risk indicators, probability distributions from option prices, and associated market sentiment indicators like the VIX. CCA provides a structural framework linking the option price information to skews in implied asset distributions and thus to credit risk.

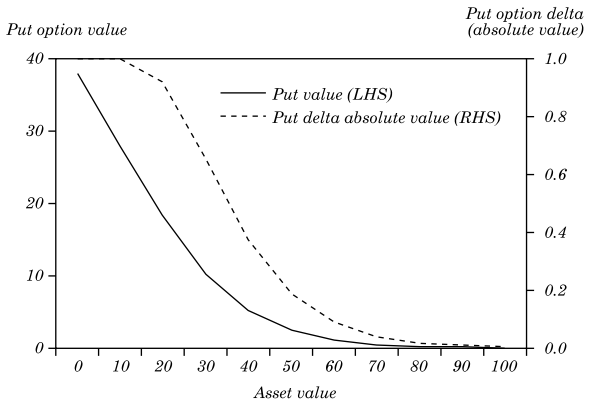
Second, the Merton Model has been extended to include stochastic interest rates. For example, Shimko, Tejima, and van Deventer (1993) include a Vasicek interest rate term structure model that allows interest rates and the term structure of interest rates to vary. This closed-form model, called the Merton-STV model, is a very useful extension that links the impact of changing interest rate levels, volatilities, and term structures to credit risk in financial institutions and corporations.

3. Measuring Risk Exposures

So far, we have discussed how to calculate the value of risky debt, guarantees, and equity using the CCA approach. We now turn to how to measure the risk exposures. The values of the contingent

claims on the CCA balance sheets contain embedded implicit options that can be used to obtain certain risk measures. These include risk exposures in risky debt, probabilities of default, distance to distress, spreads on debt, the sensitivity of the implicit options to changes in the underlying asset, and other measures. The implicit put option increases nonlinearly as the market value of the sector's assets decline.[13] The delta measures this nonlinear change in the value of an option per unit change in the value of the underlying asset, as illustrated in figure 2.

Figure 2. Implicit Put Option Value and Delta[a]



Source: Authors' computation.
a. The strike price is 40; asset volatility is 40 percent.

For example, the government's exposure to its guarantee to the banking sector can be measured with the delta of the banking sector implicit put option. There are other important sensitivity measures for risk exposures. The gamma is the change in the delta with respect to the underlying asset. The vega is the sensitivity of the change in the implicit option with respect to a change in asset volatility. These sensitivity measures of risk exposures could provide useful new indicators of the potential for financial instability.

13. See Draghi, Giavazzi, and Merton (2003).

3.1 Risk Transmission between Sectors

The framework described above is versatile and can be used to understand many types of crises and risk shifting that cannot be easily analyzed with other techniques. The risk-transmission patterns can be dampened or magnified depending on the capital structure and linkages. The framework can help identify situations in which volatility gets magnified and negative feedback loops that can trigger severe crises. The patterns of value and default correlation across different asset classes, sectors, and sovereign debt values depend on these structures and links, which are unique to a particular economy. Below are some examples of risk transmission between sectors.

3.1.1 Risk transmission from the corporate sector to the banking sector

The corporate sector's financial distress—possibly caused by stock market decline, recession, commodity price drops, or excessive unhedged foreign debt accompanied by currency devaluation—can be transmitted to the financial sector. As the value of the corporate sector's assets declines, so does the value of its debt (and equity), which leads to a decline in bank assets and an increase in banking sector credit risk. The risk transfer can thus be diagramed as follows:

$$\text{Corporate Sector} \rightarrow \text{Banking Sector}$$

The implicit put option in the banking sector derives its value from banking assets that have embedded put options in risky loans to the borrower. The household sector can similarly transmit risk to the banking sector.

3.1.2 Risk transmission from the banking sector to the government

The banking sector's financial distress, such as systemic banking crises or deposit runs, can be transmitted to the government by increasing the value of state guarantees, resulting in the following risk transfer:

$$\text{Banking Sector} \rightarrow \text{Government}$$

Banking sector distress from nonperforming loans or a deposit run can result in a large increase in the government's implicit guarantee.[14]

3.1.3 Risk transmission from the government to the banks and feedback

The government's financial distress or default can transmit risk to the financial system. For example, when the banking sector is holding a significant proportion of government securities, and there is a negative shock to the government financial position, it can have a detrimental impact on the banks. The government's implicit guarantee is also likely to increase. This, in turn, makes the government financial position even worse, which may result in the government's failure to honor its guarantee obligations and cause a collapse of the banking system.

$$\text{Government} \leftrightarrow \text{Banking/Financial System}$$

This vicious cycle could arise when the lower value of government securities reduces bank assets and raises the implicit financial guarantee, which, in turn, lowers government assets further. A similar process could occur if banks have significant lending denominated in foreign exchange and a weak government position causes a depreciation of the exchange rate: the depreciation worsens the position of the banks and thus raises the implicit guarantee, which then lowers government assets further. This means that the implicit guarantee is higher than what is shown above. In some situations, this vicious cycle can spiral out of control, eventually undermining the government's ability to provide sufficient guarantees to banks and leading to a systemic financial crisis.

3.1.4 Risk transmission from the pension system to the government

Financial distress related to pension plans can result in the transmission of risk to the government:

$$\text{Pension System} \rightarrow \text{Government}$$

14. See Merton and Bodie (1992).

We assume that the pension system is a defined benefit plan that has an implicit government guarantee. A decline in corporate assets would cause the corporate equity value to drop. This, in turn, increases the government guarantee to the pension system and the implicit guarantee to banks.[15]

3.1.5 Risk transmission from the sovereign to holders of sovereign debt

Fiscal, banking, and other problems can cause distress for the government, which can transmit risk to holders of government debt denominated in both foreign and local currencies:

Sovereign → Sovereign Debt Holders

Holders of foreign currency debt have a claim on the value of the debt minus the potential credit loss, which is dependent on the level of assets of the sovereign (in foreign currency terms) relative to the foreign currency default barrier. If debt holders demand higher spreads to cover the credit risk in government debt, then the interest rates on government debt could rise, leading to a depreciation. The associated feedback could further worsen the sovereign's financial position.

3.1.6 Risk transmission from the markets to households and consumption

Changes in the value of financial assets and real estate owned by households affect the value of household assets and have an impact on consumption:

Financial and Real Estate Markets →
Household Assets → Consumption

The CCA models for the household sector could provide useful insights into household behavior regarding consumption, especially how consumption changes with household asset volatility (and higher moments of the household asset distribution). This is because the CCA captures non-linearities in the value of household debt and in the changes in consumption.

15. See Bodie (2006).

3.1.7 Nonlinear risk transmission between sectors through implicit put options

Risk is transmitted across the sectors and balance sheets through implicit put options in risky debt and guarantees. Risky debt contains an implicit put option. If this risky debt is linked to the asset of another sector (for example, through loans from the financial sector), the risky debt of the second sector (in this case, banks) becomes a function of the implicit put option of the first sector. In other words it is a compound put option. The compound nature of the implicit put options of interlinked sectors creates the potential for highly nonlinear risk transmission. An illustration is provided in box 2.

The dynamics of the interlinked CCA risk-adjusted balance sheets provide useful insights into the asymmetric nature of value changes and risk transmission in business cycle expansions versus contractions. In a situation of rapid economic growth, asset and equity values on balance sheets trend upward. A stress event somewhere in the system can set off a chain reaction of defaults as the implicit put options are exercised. The compound nature of the implicit put options can cause a sudden sharp decline in the value of risky debt or a sharp increase in implicit guarantees. There is thus an asymmetry in the change in values in the stress or crisis period vis-à-vis the smoother rate of change in the build-up phase of the business cycle.

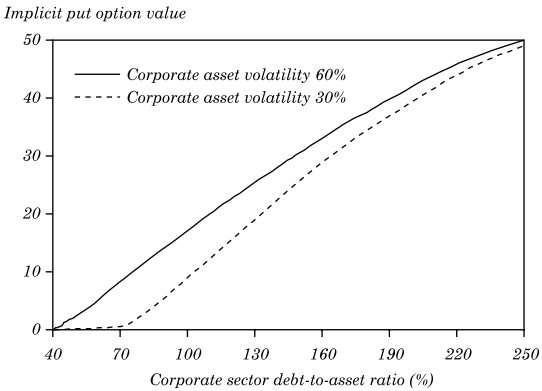
Box 2. Highly Nonlinear Risk Exposures from Interlinked Sectors

The risky debt of sector one, S1, is the default-free value of debt minus an implicit put option, which we assume is the asset of sector two, S2, that is, $(\bar{B}_{S1} - P_{S1}) = A_{S2}$. In sector two, the assets are equal to equity plus risky debt, $A_{S2} = E_{S2} + (\bar{B}_{S2} - P_{S2})$. If we combine these equations and rearrange, we see that the implicit put option, that is, the present value of expected losses associated with the debt of S2, is a function of the implicit put option in S1:

$$P_{S2} = f\left[(\bar{B}_{S1} - P_{S1}), \sigma_{A,S2}, \bar{B}_{S2}, r, t\right].$$

To illustrate this relationship, we look at bank loans to borrowers whose risky debt can be modeled as the default-free value of the loan minus an implicit put option (derived from the borrower's asset level, asset volatility, and leverage). The bank's risk exposure derives from a compound put option, since it depends on the bank assets whose value depends on the borrower's risky debt. This compound option can lead to highly nonlinear risk exposures. For example, suppose a bank's assets consist entirely of risky debt to a corporate sector with promised payments of 100. Figure B1 illustrates how the value of the bank's implicit put option increases as (i) the corporate sector debt-to asset-ratio increases; and (ii) the volatility of the corporate assets increases.

Figure B1. Bank Expected Losses (Implicit Put Option) versus Corporate Sector Debt-to-Asset Ratio for High and Low Volatility of Corporate Assets



Source: Authors' computation.

This means that the (absolute value) of the delta of the bank's implicit put option is high when the volatility of corporate assets is high, and it is high even when the corporate debt-to-asset ratio is low. While this is just a stylized example, the nonlinear nature of the implicit put options was clearly evident in the Thailand crisis. There were high levels of foreign-currency-denominated debt in the corporate sector in Thailand in 1996. In 1997, devaluation, combined with a decline in the stock market and increased volatility, led to widespread bankruptcies, which transmitted risk to bank balance sheets and to the government via the implicit guarantee. The implicit government guarantee to the banking system was 3 percent of GDP in 1996 and increased to over 35 percent of GDP following the 1997 devaluation (Gray, 2001).

3.2 Balance Sheet Risk Framework for Stress Testing, Scenario, and Simulation Analysis

The economywide CCA model can be used with scenario, simulation, and stress-testing analysis. There are different levels of sectoral aggregation, which range from the simple four sector model described here to a model with several corporate subsectors, a disaggregation of the household sector by income groups, and several financial sector divisions. The level of aggregation depends on practical issues related to data availability, data reliability, and the goals of the analysis. By simulating shocks to key variables, one can see how the CCA risk indicators and implicit put and call options are affected in other sectors.

The structure and aggregation of CCA models can be designed to analyze risk in major financial institutions for financial stability analysis. Since distress in one major institution can affect systemic stability, it makes sense to try to model the risk for major institutions individually and group smaller financial institutions to keep the model size manageable.

There are different ways to link these financial institutions to other sectors and to macroeconomic variables and use the model for stress testing. Some examples are described below.

3.2.1 Financial stability stress testing with CCA, factor, and macroeconomic models

First, a CCA model is calibrated for each major financial institution (or groups of institutions) using equity market information, and the time series of implied assets and risk indicators is calculated (calibration can be done using the Merton Model, Hull's implementation of the Merton Model, or another CCA model). The time pattern of asset returns of each financial institution (or of the risk indicators) can be used as the dependent variable in a factor model. Key factors driving these asset returns could include gross domestic product (GDP), domestic and foreign interest rates, the exchange rate, domestic and foreign equity indices, and so on. A separate macroeconomic scenario generating model, such as a macroeconomic VAR or GVAR model,[16] could then be used to test the impact of the scenarios on the key factors, which feed into the

16. Hoggarth, Sorensen, and Zicchino (2005) discuss the use of VAR models for stress testing. Pesaran, Schuermann, and Wiener (2004) and Castrén, Dees, and Zaher (2007) use GVAR models to generate scenarios for credit risk analysis.

financial institution's assets. This, in turn, affects the credit risk indicators and the value of equity capital.[17]

This stress-testing process can be summarized in four steps. Macroeconomic scenarios are generated with a VAR, GVAR model, or other model (step 1).[18] The scenarios are then used in the factor model for the bank's assets (step 2). The factor model provides the basis for estimating the impact of the scenarios on the bank's assets and its credit risk (implicit put option) (step 3) and on the bank's equity capital (step 4).

3.2.2 Banking stability stress testing with links to the corporate and household sectors

Given sufficient data on corporate and household sector balance sheets, the previous approach can be modified to first calibrate the CCA models for key financial institutions (as before) and calibrate the corporate and household sector CCA balance sheets. The next step is to use data on banks' exposure to various subsectors to provide the links between bank assets and the risky debt obligations of the borrowers. Risk is transmitted by the changing value of the implicit put options in the borrower's risky debt. A factor model could be estimated for the time series of corporate and household sector assets returns and used in conjunction with macroeconomic scenarios similar to the approach described earlier.[19]

3.2.3 Stress testing and capital adequacy assessment using CCA models of financial institutions

One major goal of financial sector stress testing is to assess the capital adequacy of various institutions under different potential shocks. Shocks to financial institution assets and asset volatility or to interest rates and other parameters can be used in the CCA model to measure the impact on capital adequacy. An advantage of using CCA models for financial institutions is that the capital adequacy can be related to asset level, asset volatility, and default probability on

17. The model used by Gray and Walsh (2008) is similar to this approach. See also Gray and Jones (2006).

18. The structural CCA model is a useful framework for understanding the comovements of assets, equity, credit risk, and key volatility measures. It could provide useful insights for structuring VAR models and designing shocks or innovations in those models.

19. Van den End and Tabbae (2005) use CCA balance sheet models and suggest links to factor models, as do Gapen and others (2004).

the institution's liabilities and other factors. Van Deventer and Imai (1997, 2003) and Belmont (2004) extend this method of calculating capital adequacy to include interest rates, interest rate volatility, and the correlation of asset returns with interest rates, using the Merton-STV model.

The financial stress tests commonly used by central banks and banking supervisors incorporate various models to measure the change in the expected default probability of the obligors, usually representative corporations or corporate subsectors. The default probabilities are then used with estimates of exposure and loss given default in a model of bank credit losses (such as Credit Risk Plus) to estimate the impact on economic capital.[20] Calibrated CCA models of financial institutions can be used to estimate capital adequacy without the need for detailed data on default probabilities or loss given default of obligors. As pointed out by van Deventer and Imai, "In the capital allocation [using the Merton-STV model], note that we didn't use the probability of default or the loss given default in allocating capital. *We don't need to*, because the probability of default and loss given default are both implied by the STV model and the value of asset volatility and interest rate and correlation" (van Deventer and Imai, 2003, p. 221). This makes CCA a potentially useful tool when detailed data on obligor exposures, default probabilities, or loss given default are not available.

3.3 Integrating Financial Risk Models and Indicators with Macroeconomic Models

Even state-of-the-art macroeconomic models generally leave out credit risk and the market risk of the claims held in agents' financial portfolios. This omission can be serious, because risk affects valuation, and changes in the valuation of agents' claims, and thus of their net worth, affects their decisions to spend, save, and invest. Recent work has begun to address the linkage of macroeconomic and financial stability models.[21]

20. See Sorge (2004). Castrén, Dees, and Zaher (2007) at the European Central Bank use the Moody's KMV median default probability for various corporate sectors with a vector autoregression (VAR) or global VAR. See also Pesaran, Schuermann, and Wiener (2004) and Alves (2005).

21. See Bardsen, Lindquist, and Tsomocos (2006), Goodhart, Sunirand, and Tsomocos (2004, 2006a, 2006b), Tsomocos (2003), Haldane, Hall, and Pezzini (2007), Swinburne (2007), and IMF (2007).

To understand the interaction of balance sheet risk and the macroeconomy, a promising area of future research is the integration of the financial risk analytic models and indicators with traditional macroeconomic models. Such integrated models need to address the different mathematical nature of macroeconomic models and finance models. Macroeconomic models are primarily stock-flow models in discrete time and are usually geared to forecasting the mean of macroeconomic variables. Financial risk analytics, on the other hand, focus on the probability that assets, following a random walk, will fall below a certain threshold or default barrier, such that volatility (the second moment) rather than the mean (first moment) is the critical element in risk analysis. The CCA framework centers on volatile assets relative to a distress barrier, using option pricing concepts to calculate credit risk indicators. While there can be different levels of aggregation of the CCA balance sheets, whatever level of aggregation is chosen, the time pattern of the following could be calculated and used with macroeconomic models:

—Time series of CCA balance sheet components (namely, assets, asset volatility, distress barriers, and implicit put and call options) and sensitivity measures (such as delta and vega);

—Time series of CCA-derived credit risk indicators (including distance to distress, estimated default probability, and CCA credit spreads) (see box 3 for ways to aggregate credit risk indicators); and

—Time series of market indicators such as observed CDS and bond spreads or market risk appetite indicators (for example, VIX).

These financial risk analytic measures can be related to the time pattern of macroeconomic variables using econometric techniques to study leads, lags, or contemporaneous correlation. Various channels could be investigated using econometrics. For example, the channel from GDP to corporate and household risk indicators and then to financial sector risk indicators could be modeled. The reverse channel from the financial sector (balance sheets and risk indicators) to the corporate and household sector balance sheet components and to risk indicators, and the relationship to GDP over the economic cycle, could similarly be investigated.[22]

22. The dynamics of corporate and household borrowing levels are directly related to distress barriers in the CCA model.

Box 3. Aggregation of Credit Risk Indicators (CRIs)

The CCA credit risk indicators of a portfolio of individual financial institutions (or corporate firms) must be aggregated to provide a tractable measure of system risk for use with macroeconomic models and for financial stability analysis. There are several ways to measure the system risk by aggregating the risk indicators of individual banks or institutions.

—Weight the individual default probabilities (that is, the EDFs from Moody's KMV or other default probability estimate) by the implied assets of each bank or financial institution to get a system risk indicator.

—Weight the distance to distress for each institution by the implied assets of each bank or financial institution to get a system risk indicator.

—Use the median EDF for the subsector or group, for example, as calculated by Moody's KMV.

—Sum the implicit put options of a portfolio of institutions to calculate the system expected loss for a given horizon.

—Calculate an *N*th-to-default indicator: the time pattern of default risk indicators for a portfolio of individual financial institutions can be used to understand the default correlations and get a credit risk indicator that is the probability of *N* defaults over a specific horizon.

—Calculate the joint distribution of default probabilities in a portfolio of financial institutions, such as the joint probability modeled with the portfolio multivariate density developed by Segoviano (2006) and Segoviano, Goodhart, and Hofmann (2006).

3.4 Financial Risk Analytic Indicators and Monetary Policy Models

Financial stability models and monetary stability models, by their nature, are very different frameworks. There is keen interest in relating these two types of analysis, but no consensus on how it can be done. The primary tool for macroeconomic management is the interest rates set by the central bank. Simple model-based monetary policy models are widely used by central banks to understand macroeconomic and interest rate relationships.[23] A simple four module monetary policy model of this type consists of an equation for the GDP output gap, an equation for inflation, an equation for the exchange rate and real interest rates, and a Taylor rule for setting the domestic policy

23. Berg, Karam, and Laxton (2006a, 2006b) provide a good summary.

rate. The domestic policy rate is a short-term interest rate set by the central bank, such as the Federal funds rate in the United States.

Since the economy and interest rates affect financial sector credit risk, and the financial sector affects the economy, an important issue is whether credit risk indicators (or CRIs, described in box 3) should be included in monetary policy models and, if so, how. Including an aggregate credit risk indicator in the GDP gap equation and testing whether or not the coefficient is an important first step toward a better understanding of how financial sector credit risk affects GDP. The next step could be to add a fifth equation relating the CRIs to GDP and interest rates (possibly drawing on analysis from the previous section relating financial risk indicators to macroeconomic variables).

Past data could be used to include the CRI in the policy rate reaction function, to examine whether financial stability was taken into account when setting interest rates in the past. A variation of this approach is being investigated in the research department of the Central Bank of Chile.[24] The approach taken in the Central Bank of Chile is to first estimate the distance to distress for the banking system (each individual bank's distance to distress, from a CCA model that is weighted by bank implied assets). The banking system's distance to distress is included in the GDP gap equation and in the policy rate reaction function. The model parameters are then estimated using historical data, including the distance-to-distress indicator. This approach can be used to examine the tradeoffs between GDP, inflation, and the banking system's distance to distress.[25]

Outputs of the sovereign CCA model include an estimate of the risk premium on government local currency debt, which is embedded in the nominal interest rate. This, in turn, affects the exchange rate, which is part of the GDP gap and inflation equations (the first and second equations in the simple monetary policy model). This issue is important for certain emerging market countries (such as Brazil and Turkey).[26] These are promising areas for further research.[27]

24. See Gray, García, Luna, and Restrepo (in this volume).

25. A related issue is whether an indicator of market risk appetite such as the VIX should be included in monetary policy models along with the credit risk indicator. This could help estimate the impact of the credit risk indicator on the GDP gap, adjusted for changes in risk appetite.

26. See Gray and Malone (2008) and Favero and Giavazzi (2003).

27. Other interesting routes for linking risk analytics more closely with macroeconomic models include incorporating default risk and a risk premium into the Mundell-Fleming model to separate out the effects of changes in interest rates due to changes in the market for liquidity and changes in interest rates due to changes in the risk premium on debt (see Gray and Malone, 2008).

A final point involves the feedback of monetary policy and changes in interest rates on the CCA balance sheet values and risk indicators. CCA models that incorporate changes in interest rates (such as the Merton-STV model or the factor model for asset return with interest rates as one factor) can be used to estimate the second round effects on the credit risk of financial institutions in response to changes in interest rates.

4. Conclusions

This paper proposes a new approach to improve the way central banks analyze and manage the financial risks of a national economy. It is based on the modern theory and practice of contingent claims analysis (CCA), which is successfully used today at the level of individual banks by managers, investors, and regulators. The basic analytical tool is the risk-adjusted balance sheet, which shows the sensitivity of the enterprise's assets and liabilities to external shocks. The sectors of an economy are viewed as interconnected portfolios of assets, liabilities, and guarantees—some explicit and others implicit. The CCA approach is well-suited to capturing such nonlinearities and to quantifying the effects of asset-liability mismatches within and across institutions. Risk-adjusted CCA balance sheets facilitate simulations and stress testing to evaluate the potential impact of policies to manage systemic risk. The time pattern of CCA balance sheet components, risk indicators, and sensitivity parameters can be integrated with macroeconomic models. Finally, the paper explored the inclusion of financial system risk indicators and other financial risk parameters in simple monetary policy models.

APPENDIX

This appendix provides details on estimating implied assets and asset volatility, and extensions of the Merton Model.

A1. Calculating Implied Assets and Implied Asset Volatility

The value of assets is unobservable, but it can be implied using CCA. In the Merton Model for firms, banks and nonbank financial institutions with traded equity use equity, J, equity volatility, σ_j, and the distress barrier in the following two equations to solve for the two unknowns A, asset value, and σ_A, asset volatility (see Crouhy, Galai, and Mark, 2000).

$$J = A_0 N(d_1) - \bar{B} N(d_2)$$

and

$$J\sigma_J = A\sigma_A N(d_1).$$

A2. Extensions of the Merton Model

Numerous extensions of the original Merton Model have been developed that relax certain assumptions in the original model. Restrictions of the model include the assumptions that: (i) default can occur only at the maturity date of the debt; (ii) there is a fixed default barrier; (iii) there is a constant risk-free rate; and (iv) asset volatility is constant. Cossin and Pirotte (2001) provide a good summary of extensions of the Merton Model. Black and Cox (1976) extend the Merton Model to relax the assumptions (i) and (ii) above by introducing a first-passage-time model where default can occur prior to the maturity of the debt if the asset falls below a specified barrier function for the first time.

Although the strict theoretical condition in the Merton Model for default is that the value of assets is less than the required payments due on the debt, in the real world, default typically occurs at much higher asset values, either because of a material breach of a debt covenant or because assets cannot be sold to meet the payments (so-called inadequate liquidity) or because the sovereign decides

to default and induce a debt renegotiation rather than sell assets. To capture these real-world conditions for default in the model, we specify a market value of total assets at which default occurs. We call this level of assets that trigger default the distress barrier. This barrier can be viewed as the present value of the promised payments discounted at the risk-free rate. The approach used in the KMV model sets the barrier level equal to the sum of the book value of short-term debt, promised interest payments for the next 12 months, and half of long-term debt (see Crouhy, Galai, and Mark, 2000; Crosbie, 1999, 2001).

In the 1990s, the KMV model was based the Vasicek-Kealhofer (VK) model, which has multiple layers of liabilities and several confidential features. Moody's KMV's expected default frequency (EDF) credit measure is calculated using an iterative procedure to solve for the asset volatility. This distance to distress was then mapped to actual default probabilities using a database of detailed real-world default probabilities for many firms. The Moody's KMV distance to distress and the cumulative expected default probabilities (CEDF) are calculated as follows:

$$DD_{KMV} = f\left[\frac{\ln(A_0/B_t) + (\mu_A - \sigma_A^2/2)t}{\sigma_A\sqrt{t}}\right]$$

and

$$CEDF_t = f\left[DD_{KMV}(t)\right].$$

This definition of DD_{KMV} includes the real drift of the asset, μ_A, whereas the distance to distress from the Merton approach has r for the asset drift. Since Moody's KMV estimates the actual default probabilities, the risk-neutral default probabilities are calculated from the correlation of the implied asset with the market, the market Sharpe Ratio, and time horizon.

The CreditGrades (2002) model includes a diffusion of a firm's assets and a first-passage-time default with a stochastic default barrier. The model was modified to incorporate equity derivatives (Stamicar and Finger, 2005). Hull, Nelken, and White (2004) study the relationship between the volatility skew implied by equity options and CDS spreads. They establish a relationship between implied volatility of two equity options, leverage, and asset volatility. This approach is, in fact, another way of implementing Merton's model to

get spreads and risk-neutral default probabilities directly from the implied volatility of equity options. Zou (2003) discusses a similar approach using several equity options.

The Merton Model has been extended to include stochastic interest rates, as well. Shimko, Tejima, and van Deventer (1993) include a Vasicek interest rate term structure model that relaxes assumption (iii) above, allowing the risk-free interest rate to change and including the correlation of asset return with the interest rate. There are two stochastic factors, the asset and the interest rate. This closed-form model, which is frequently called the STV model, is a very useful extension because it includes the impact of changing interest rate term structures. Longstaff and Schwartz (1995) take the Black and Cox (1976) model and add in stochastic interest rates, similar to the way the STV model includes interest rates.

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Incorporating Financial Sector Risk into Monetary Policy Models: Application to Chile

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This article analyzes whether market-based financial stability indicators (FSIs) should be included in monetary policy models and, if so, how.[1] Since the economy and interest rates affect financial sector credit risk, and the financial sector affects the economy, this article builds a model of financial sector vulnerability and integrates it into a macroeconomic framework, typically used for monetary policy analysis. More specifically, should the central bank explicitly include the financial stability indicator in its monetary policy (interest rate) reaction function? This is the most important question to be answered in this article. The alternative would be to react only indirectly to financial risk by reacting to inflation and gross domestic product (GDP) gaps, since they already include the effect that financial factors have on the economy.[2]

We thank Rodrigo Alfaro, Nicolas Magud, Jorge Chan-Lau, as well as the conference participants for useful comments and suggestions.

1. The term FSI used here is an indicator derived from forward-looking market information, including indicators from the contingent claims analysis model. It should not be confused with the accounting ratio financial stability indicators.

2. An alternative could be designed in which the central bank only reacts directly to financial risk whenever the financial stability indicator breaches a predetermined threshold.

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The integration of the analysis of financial sector vulnerability into macroeconomic models is an area of important and growing interest for policymakers, in both developed and emerging markets. Monetary policy models and financial stability models, by their nature, are very different frameworks. Monetary policy models are widely used by central banks to understand the transmission mechanisms of interest rates to the macroeconomy and inflation. On the other hand, coherently estimating the effect of shocks to vulnerability on banks' risk requires both a model of banking sector risk and a tractable methodology for simulating shocks and estimating their effect on various risk measures.

Market-based financial stability indicators summarize both the credit channel and credit risk transmission from distressed borrowers in the economy. Market-based FSIs provide information on the banking sector's financial condition, which is related to the quantity of credit extended and the possible or expected effects of this channel on the real economy and GDP (that is, credit expansion and the financial accelerator).[3] Market-based FSIs also capture the reduced financial soundness of banks when borrowers default in periods of economic distress, which lowers the value of risky debt and thus reduces banking sector assets and increases banking asset volatility. This is a reflection of the economic condition of borrowers and of the real economy. (Note that when the banking sector is in distress, bank assets and bank equity values are lower and the volatility of bank assets and bank equity is much higher).

Among the different choices for the market-based FSIs, in this paper we use distance to default of the banking system, which is an indicator of the riskiness of banks estimated from the contingent claims analysis (CCA) tools developed in finance. The basis of CCA is that the liabilities of a financial institution or firm derive their value from assets that are stochastic. The expected variation (volatility) of assets over a future horizon, relative to the promised payments on liabilities, provides a measure of financial distress risk. CCA methodology is frequently used to estimate the probability that an entity (in our case, banks, but also corporations or even governments) will default on its obligations. CCA's explicit

3. Bernanke, Gertler, and Gilchrist (1999) introduced financial frictions into a business cycle model, starting a fertile field of macroeconomic research. The relation of monetary policy and financial stability is discussed in Walsh (2009) and the literature surveyed therein.

focus on risk and the probability of default or distress and its link to market prices of equity have many advantages. Equity data by nature incorporate the forward-looking expectations of the market in a way that static indicators of bank risk, such as nonperforming loan ratios and provisioning, cannot. The high frequency of observations, at least for equity and interest rate data, allows for much faster updating of risk measures than is possible with data that are available only at monthly or quarterly frequencies. The CCA financial risk indicators are calculated for individual banks and then can be aggregated into a systemwide financial stability indicator.

The CCA systemwide FSI is modeled jointly with a practical five-equation dynamic stochastic macroeconomic model used to set monetary policy. The macroeconomic model was developed at the Central Bank of Chile at the start of the implementation of fully fledged inflation targeting in 2000 (García, Herrera, and Valdés, 2002), and it closely resembles the one proposed by Berg, Karam, and Laxton (2006) as a useful toolkit applicable to the analysis of monetary policy in many small open economies. As they claim, "in the new Keynesian synthesis, there has been a convergence between the useful empirically motivated IS/LM models developed in several policymaking institutions and dynamic stochastic general equilibrium approaches that take expectations seriously and are built on solid microeconomic foundations."[4]

The specific model used here consists of an equation for the output gap (IS), another for inflation (Phillips curve or aggregate supply), an equation for the exchange rate (interest parity condition), a yield curve relating short- and long-run interest rates, and the Central Bank reaction function (Taylor rule). Indeed, the primary tool for macroeconomic management is the interest rate set by the central bank as a reaction to the deviations of inflation from the target and the output gap (Taylor, 1993). Most equations are forward looking in the sense that they include the expected levels of the dependent variables on the right hand side.

In addition to the macroeconomic equations, we include a CCA module that interacts with the macroeconomic equations, and they affect each other in several ways. For instance, the output gap includes distance to default as an indicator of financial risk in order to analyze whether it is significant or not. Including an aggregate

4. Berg, Karam, and Laxton (2006a, p. 3).

indicator of distance to default—and credit risk in the GDP gap equation and testing whether the coefficient is significant is a first step to get a better understanding of how financial sector credit risk affects GDP. The system is perfectly endogenous given that the interest rate and GDP influence the level and volatility of banks equity, while at the same time distance to default affects the country risk premium, GDP, and the exchange rate. The model contains a steady state to which the variables converge, thanks to the reaction of monetary authorities.

Finally, to assess the inclusion of risk indicators in the monetary authorities' reaction function, we construct efficiency frontiers mapping inflation and output volatilities after the artificial economy is hit with stochastic shocks drawn from a normal distribution. In general, we conclude that it is more efficient to include distance to default in the reaction function, because it enables the central bank to reduce the volatility of both inflation and output. Moving the policy interest rate more than is warranted by the gaps of only inflation and output is efficient because negative shocks to asset prices and liquidity could end up in a credit risk crisis, with negative systemic consequences for the financial system and production.[5]

Section 1 presents the background of CCA distance to default and discusses the data used in the analysis. Section 2 lays out the macroeconomic framework, as well as the equations required to simulate distance to default, which are included in the macroeconomic setting. Section 3 presents the results of the simulations, and, section 4 concludes and presents possible extensions in this line of research.

1. Risk Measures from Contingent Claims Analysis

This section introduces the contingent claims approach (CCA), which uses forward-looking information to build risk indicators for the banking system, and have important implications, for monetary policy, as will be clear in the third section This approach provides a methodology to combine balance sheet information with widely used finance and risk management tools to construct marked-to-market balance sheets that better reflect underlying risk. The risk-adjusted balance sheets use option pricing tools to value the liabilities, which are modeled as claims on stochastic assets. The approach can be

5. On the other hand, a very large distance to default could reflect bubbles in asset prices, which usually have bitter endings.

used to derive a set of risk indicators, including distance to default, that can serve as barometers of risk for firms, financial sector vulnerability, and sovereign risk.

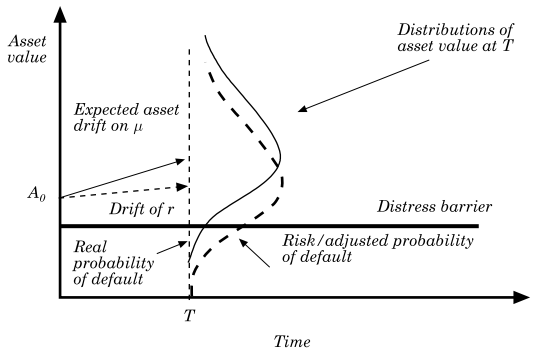
A contingent claim is any financial asset whose future payoff depends on the value of another asset. The prototypical contingent claim is an option—the right to buy or sell the underlying asset at a specified exercise price by a certain expiration date. A call is an option to buy, and a put is an option to sell; the value of each is contingent on the price of the underlying asset to be bought or sold. Contingent claims analysis is a generalization of the option pricing theory pioneered by Black and Scholes (1973) and Merton (1973). Since 1973, option pricing methodology has been applied to a wide variety of contingent claims. In this paper we focus on its application to the analysis of credit risk and guarantees against the risk of default, together with their links to macroeconomic and financial developments.

The contingent claims approach is based on three principles: the values of liabilities are derived from assets; liabilities have different priority (that is, senior and junior claims); and assets follow a stochastic process. The liabilities consist of senior claims (such as senior debt), subordinated claims (such as subordinated debt), and junior claims (equity or the most junior claim). For a bank, as the value of its total assets decline, the debt that it owes to other institutions becomes riskier, and its value declines, while the credit spreads on its risky debt rise.

Balance sheet risk is the key to understanding credit risk and the probability of crisis. Default happens when assets cannot service debt payments, that is, when assets fall below a distress barrier comprising the total value of the firm's liabilities. Uncertain changes in future asset value, relative to promised payments on debt, is the driver of default risk. Figure 1 illustrates the key relationships. The uncertainty in asset value is represented by a probability distribution at time horizon T. At the end of the period, the value of assets may be above the promised payments, indicating that debt service can be made, or below the promised payments, leading to default. The area below the distribution in figure 1 is the "actual" probability of default. The asset-return probability distribution used to value contingent claims is not the "actual" one, but the risk-adjusted or risk-neutral probability distribution, which substitutes the risk-free interest rate for the actual expected return in the distribution. This risk-neutral distribution is the dashed line in figure 1, with

expected rate of return r, the risk-free rate. Thus, the risk-adjusted probability of default calculated using the risk-neutral distribution is larger than the actual probability of default for all assets that have an actual expected return (μ) greater than the risk-free rate r (that is, a positive risk premium).[6]

Figure 1: Distribution of Asset Value and Probability of Default



Source: Adapted from Gray and Malone (2008).

The actual probability of default can be calculated by combining the CCA/Merton model with an equilibrium model of underlying asset expected returns to produce estimates that are consistent for expected returns on all derivatives, conditional on the expected return on the asset. One does not have to know expected returns to use the CCA/Merton model for the purpose of value or risk calculations, but such data are necessary for calibrating into actual probabilities. The value of assets at time t is A*(t)*. The asset return process is

$$\frac{dA}{A} = \mu_A dt + \sigma_A \varepsilon \sqrt{t},$$

where μ_A is the drift rate or asset return, σ_A is equal to the standard deviation of the asset return, and ε is normally distributed, with zero mean and unit variance.

6. See Merton (1992, pp. 334–43; 448–50).

Default occurs when assets fall to or below the promised payments, B_t. Therefore, B_t is the price at which the option is exercised. The probability of default is the probability that $A_t \leq B_t$, which is

$$\begin{aligned}\text{Prob}(A_t \leq B_t) &= \text{Prob}\left\{A_0 \exp\left[(\mu_A - \sigma_A^2/2)t + \sigma_A \varepsilon\sqrt{t}\right] \leq B_t\right\} \\ &= \text{Prob}(\varepsilon \leq -d_{2,\mu}).\end{aligned}$$

Since $\varepsilon \sim N(0,1)$ the "actual" probability of default is $N(-d_{2,\mu})$, where

$$d_{2,\mu} = \frac{\ln(A_0/B_t) + (\mu_A - \sigma_A^2/2)t}{\sigma_A\sqrt{t}}$$

is distance to default with a drift of μ_A and $N(\bullet)$ is the cumulative standard normal distribution.

The probability distribution at time T is shown in figure 1 above (dashed line) with drift of the risk-free interest rate, r. The risk-adjusted probability of default is $N(-d_2)$, where

$$d_2 = \frac{\ln(A_0/B_t) + (r - \sigma_A^2/2)t}{\sigma_A\sqrt{t}}.$$

This is distance to default with a drift of r, the risk-free rate.

1.1 Calculating Implied Assets and Implied Asset Volatility

The value of assets is unobservable, but it can be implied using CCA. In the Merton model for firms, banks, and nonbank financial entities with traded equity, use equity, E, equity volatility, σ_E, and the distress barrier in the following two equations to solve for the two unknowns A, asset value, and σ_A, asset volatility (see Crouhy, Galai, and Mark, 2000). The first equation is the equation for equity, E, valued using the Black-Scholes-Merton formula for pricing call options:

$$E = AN(d_1) - B\exp(-r \cdot t)N(d_2).$$

The second equation relates the volatility and value of equity to the implied volatility and value of assets (Merton 1973, 1974):

$$E\sigma_E = A\sigma_A N(d_1),$$

where d_2 was already defined and $d_1 = d_2 + \sigma_A\sqrt{t}$. Since there are two equations and two unknowns (asset value, A, and asset volatility, σ_A), an iteration procedure is used to find the values of the unknowns. In practice, d_1 and d_2 can be calculated because they depend on A and σ_A.

Financial fragility is intimately related to the probability of default. Shocks to prices or liquidity frequently end up being converted into credit risk crises, as banks' debtors see their income flows weaken and thus run into difficulties servicing their loans to banks. Default is hard to handle in traditional macroeconomic models in part because of assumptions that usually exclude such a possibility. In addition, flow-of-funds accounts and accounting balance sheets cannot provide measures of risk exposures that are forward-looking estimates of losses. CCA, on the other hand, is a framework that explicitly includes and estimates the probability of default.

Since there is a nonzero chance of default, the value of debt is risky and therefore less than the value of risk free debt:

$$\text{Risky debt} + \text{Guarantee against default} \equiv \text{Risk-free debt}.$$

The value of risky debt can therefore be modeled as the default-free value of the debt less the expected loss:

$$\text{Risky debt} \equiv \text{Risk-free debt} - \text{Guarantee against default}.$$

Given that this guarantee is an asset of uncertain value, the debt can be thought of and modeled as a contingent claim.

This identity holds both conceptually and in terms of value. If the debt is collateralized by a specific asset, then the guarantee against default can be modeled as a put option on the asset with an exercise price equal to the face value of the debt. The debt holder is offering an implicit guarantee, as it is obligated to absorb the losses if there is default. However, often a third party is the guarantor, as is the case when the government guarantees the deposit liabilities of banks or the pension-benefit promises of firms.[7]

7. The CCA framework is an extension of Merton's models of risky debt (1974) and deposit insurance (1977).

Using the Black-Scholes-Merton differential equation for pricing contingent claims (shown above), the value of risky debt is a function of the default-free value of debt (that is, the distress barrier) at time 0, the asset level at time 0, the volatility of the asset, the time horizon until the expiration date of the claim, and the risk-free interest rate. Since 1973, the Merton methodology has been applied to a wide variety of corporations and financial institutions, as well as sovereigns.

Banks do not frequently default, and regulators are likely to be less interested in the probability of such an event than they are in the possibility that bank assets will fall below a level at which the authorities might be expected to intervene.[8] One useful threshold is a minimum capital threshold. This barrier would be the default barrier plus, say, 8 percent of assets. The CCA model can be used in this analysis. This model would give the distance to minimum capital as well as the distance to default. Appendix A provides some extensions of the CCA model.

1.2 Calculating Risk Indicators for Individual Banks or Financial Institutions

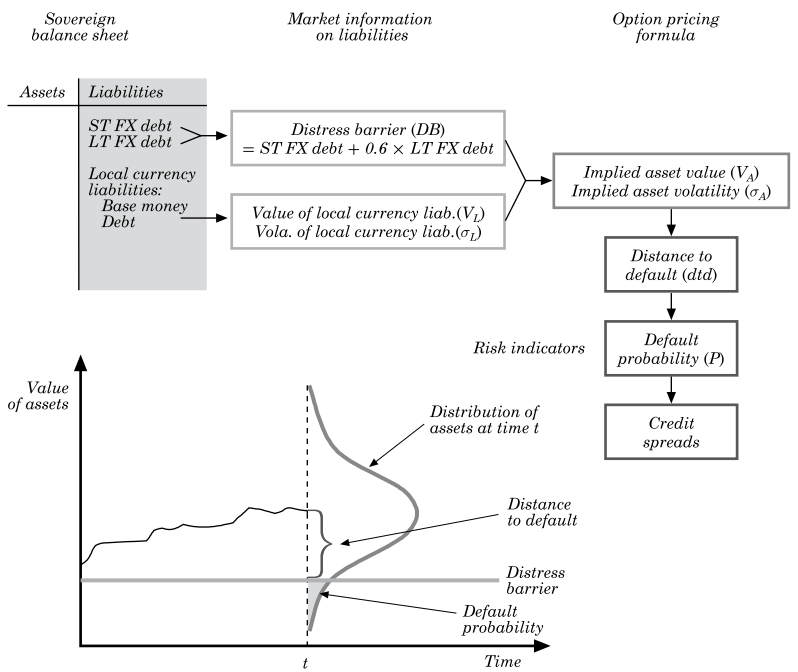
Domestic equity markets provide pricing and volatility information for the calculation of implied assets and implied asset volatility in corporate, bank, and nonbank financial institutions. The simplest method solves two equations for two unknowns, asset value and asset volatility. Details are shown in Merton (1974) and Crouhy, Galai, and Mark (2000). Levonian (1991) uses explicit option prices on bank equity to measure equity volatility and calibrate Merton models for banks. Moody's KMV has successfully applied its version of the CCA model to measure the implied asset values and volatilities and to calculate expected default frequencies (EDFs) for over 35,000 firms and financial institutions in 55 countries around the world (KMV Corporation, 1999 and 2001).

For unlisted corporate entities and banks, the relationship between the accounting information and risk indicators of companies with traded equity can be used as a guide for mapping accounting information to default probabilities and risk indicators for institutions that do not have traded equity. (An example is Moody's RiskCalc for corporate sectors in many countries and for banks in the United States.).

8. The model's condition of infrequent default was not the case for many banks in the subprime crisis.

The CCA model for banks and financial institutions uses a time series of the daily market capitalization, the volatility of the market capitalization, and the distress barrier (derived from book values of deposits and debt) to estimate a time series of the implied market value of bank assets and asset volatility. Several useful risk indicators can be calculated for each bank or institution, including distance to default; the risk-adjusted and actual probabilities of default; the expected losses (put option) to depositors and debt holders; the potential size of public sector financial guarantees; and the sensitivity of risk indicators to changes in underlying bank assets, asset volatility, or other factors. The steps used to calculate the implied assets and asset volatility of the individual bank or financial institution, and the risk indicators, are shown in figure 2.

Figure 2. Calibrating Bank CCA Balance Sheets and Risk Indicators



Source: Adapted from Gray and Jones (2006).

1.3 A Distance-to-Default Indicator for Chile

The strategy to compute a risk indicator based on the CCA model described in the previous sections was applied for Chile. The indicator was computed by treating the portfolio of banks in the system as one large bank. Since not all banks have shares quoted in the stock market, a sample of the largest banks was used, including approximately 50 percent of total bank assets, 65 percent of the total amount of bonds issued by the banking system, and more than 80 percent of the market capitalization of the banking industry.[9] The market capitalization, the volatility of the market capitalization, and the default-free value of debt (derived from book values of deposits and debt) were then used to simultaneously estimate a time series of the implied market value of bank assets and asset volatility (Gray, Echeverría, and Luna, 2007).

Although we include 80 percent of bank equity, there could be a bias given that we exclude small banks, which could be riskier. Nevertheless, when Luna and Gómez (2008) compare an aggregated risk indicator with an aggregation of individual indicators, they conclude that behavior is very similar in terms of levels and volatility. The authors further state that contagion through interbank lending would be very limited since it represents a small share of total assets. Moreover, the introduction of a real time gross settlement (RTGS) system in Chile substantially reduced settlement risks.[10] Still, using ad hoc methods of aggregating data from different banks can lead to mismeasurement of systemic risk, by averaging heterogeneous agents and, implicitly, assuming that the measures of different banks' risks are not correlated. Consequently, the methodology should be used as a complement to the regular stress tests for banks and adequate surveillance analysis of the risks for banks' financial stability.

To get a daily estimate of total bank assets, an implicit value was obtained by calculating their debt and net worth. Since it is not feasible to get the market value of their short- and long-run debt, it is common to extract their book value, which, due to current regulation in Chile, is very close to the market value—provided there is no financial turmoil. Total debt includes monthly information supplied

9. See Gray, Echeverría, and Luna (2007, table 1).

10. For simplicity, we did not consider explicitely the volatility of foreign debt. Nevertheless, in Chile, banks' foreign debt in the analyzed period represented only 7 percent of total debt.

by the Superintendency of Banks and Financial Institutions (SBIF) on short-term debt plus a portion of long-term debt.[11]

Nevertheless, the volatility of interest rates could imply that the market value of debt fluctuates around the book value. These fluctuations are higher for longer maturities, which in our calculation are less important. To correctly measure the market value of debt we would need to have an asset pricing model with two stochastic processes, where the interest rates affect the value of bank assets and equity. In the current setting, we are implicitly assuming that interest rates are nonstochastic. We thus have only one stochastic process, namely, bank assets.

On the equity side, daily numbers of shares and their prices for the selected banks were obtained from the Santiago Stock Exchange. However, we cannot calculate implicit equity volatility from call options on bank shares because such derivatives do not exist in Chile. We therefore obtained a direct measure of stock volatility with a simple model of conditional heteroskedasticity, with a one-year horizon.[12] Recent work on this issue shows that at least for the S&P500, the volatility obtained with a similar model is highly correlated with the VIX, which is computed based on the implicit volatility from options on the stocks included in this index (Alfaro and Silva, 2008).

In theory, share prices should equal the present discounted value of the flow of dividends. In practice, these prices could also change as a result of many factors other than movements in fundamentals, namely, abundant liquidity, market overreactions to good news, herd behavior, or a different risk assessment than that of the authorities.

Despite all the caveats mentioned above, indicators based on the behavior of market prices have proved to be good predictors of financial stress, risk ratings, and several credit risk indicators.[13] Several studies show that the model is robust, since it correctly reflects and anticipates the behavior of other measures of banks' financial fragility, such as risk ratings and various indicators of

11. A linear transformation of the balance sheet data is performed to generate daily data.

12. Echeverría, Gómez, and Luna (2008) include a detailed analysis of measuring distance to default, in which they consider alternative strategies to obtain direct volatility.

13. Tudela and Young (2003) find that the distance-to-default measure anticipates changes in the risk ratings of banks in Europe.

portfolio quality.[14] Thus, distance to default is still a very good complement to the monitoring of systemic risk.

We use the information on equity and debt to compute the implicit value of assets and its volatility with the Black-Scholes-Merton system described above, in order to solve the system of nonlinear equations for asset and asset volatility (Gray, Merton, and Bodie, 2006). However, the value of assets and their volatility require the calculation of d_1 and d_2, the latter being an exact measure of distance to default (*dtd*). Therefore, in practice this system is complemented by two additional equations, one for d_1 and another for d_2, and solved simultaneously to obtain A_0, σ_A, d_1, d_2, as well as $N(-d_2)$, which corresponds to the probability of default.

An illustrative approximation to *dtd* could be computed by defining it as the difference between the implicit market value of assets (A) and the distress barrier (DB), divided by one standard deviation of the value of assets: $dtd \approx (A-DB)/A\sigma_A$. This indicator corresponds to the number of standard deviations from the current level of assets to the distress barrier, given the level of equity and its volatility, the distress barrier, the interest rate, and the period analyzed. The larger this indicator, the safer is the banking system. It is also possible to compute the probability of default with this formula under the assumption that *dtd* is normally distributed.

Figure 3 shows the time pattern of *dtd* for the Chilean banking system estimated with the Black-Scholes-Merton approach from 1997 to 2006, along with a three-month moving average.[15] The period of highest risk for the banking system coincides with the fallout from the Long-Term Capital Management (LTCM) and Russian crises, between late 1998 and early 1999. Since then, the Chilean banking system has gradually reduced its risk, though this trend appears to have leveled off in late 2005.[16] Other periods in which markets assessed suddenly higher risk for the Chilean banks include the

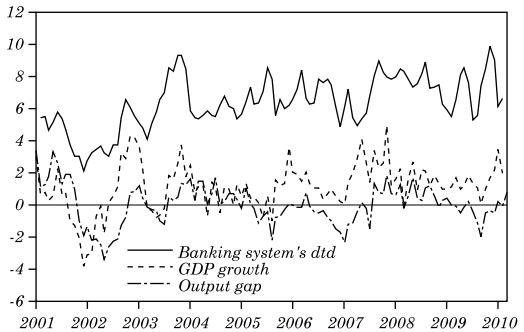
14. See Chan-Lau (2006), Chan-Lau and Gravelle (2005), and Chan-Lau, Jobert, and Kong (2004).

15. The CCA risk indicators shown in figure 3 are taken from Gray, Echeverría, and Luna (2007), who use daily market capitalization for the banks obtained by the Central Bank of Chile from the Santiago Stock Exchange. Bank debt was obtained from the Central Bank of Chile's database. Financial practitioners use various methods for estimating the volatility of daily asset returns. Two frequently used methods model daily volatility either as a GARCH(1,1) or as a moving average process. The GARCH(1,1) methodology for all banks in the sample was used in this case, but the results of the moving-average model are similar.

16. This leveling off has occurred at a very low level of risk, as shown below.

decline in world stock markets following the collapse of the internet bubble in 2000 and the period preceding the Brazilian presidential elections in the third quarter of 2002.

Figure 3. Distance to Default for the Banking System



Source: Authors' calculations.

Figure 3 also illustrates that there is a relation between the banking system's distance to default and both annual GDP growth and the output gap. The regressions with output and the output gap as the dependent variable, with *dtd* as one of the independent variables, are shown in appendix B. Distance to default has a significant impact on both output and the output gap. Other systemic risk indicators are described in detail in Gray, Merton, and Bodie (2007, 2008), Goodhart, Sunirand, and Tsomocos (2006a, 2006b), Gray and Walsh (2008), Gray and Malone (2008), Haldane, Hall, and Pezzini (2007), Segoviano (2006), and Segoviano, Goodhart, and Hofmann (2006).

2. Linking Macrofinance Indicators to A Simple Dynamic Stochastic Macroeconomic Policy Model

In this section, we lay out an integrated macrofinance policy model in which risk indicators for the financial system as a whole are incorporated directly into a macroeconomic policy model. Our focus here is on a modular exposition of the parts of the model and the equations that make up these parts, as well as giving intuition for how they are linked together and can be used for the analysis of a wide range of policies.

Examples of forward-looking indicators of systemic risk derived from the contingent claim analysis (CCA) model are distance to default (*dtd*), expected loss (that is, an implicit put option), or the default probability weighted by the assets of individual financial institutions. The macroeconomic model used here incorporates the CCA risk indicator *dtd*, whose derivation is described below.[17]

The first module of our model consists of equations for the most important macroeconomic variables. There is an equation for the output gap, an equation for inflation, an equation the real exchange rate, a yield curve, and a Taylor rule for setting the domestic policy rate, which is a short-term interest rate set by the central bank. The second module is used to model distance to default.

Distance to default for the banking system is included in the GDP gap equation, the parity condition, and the policy rate reaction function. The model parameters are estimated using historical data, including the distance-to-distress indicator. Although the equations have empirical support (as shown in appendix B), this is mostly a theoretical exercise in which some of the model parameters are modified (calibrated) to assess how the simulation results change with them. The approach can be used to examine the tradeoffs between GDP and inflation, with and without the inclusion of distance to distress for the banking system in the monetary authorities' reaction function.[18]

2.1 Module 1: Output, Inflation, the Exchange Rate, and a Taylor Rule

The five-equation dynamic stochastic macroeconomic model used to set monetary policy was already briefly described. This model, which is close to the one by Berg, Karam, and Laxton (2006a, 2006b), is a version of the model that was built in the Central Bank of Chile

17. A related issue is whether an indicator of market risk appetite, such as the VIX, should be included in monetary policy models along with the risk indicator. This could help estimate the impact of the credit risk indicator on the GDP gap, adjusted for changes in risk appetite. In addition, risk indicators for a group of institutions could include the correlation, or dependence structure, observed between the institutions.

18. Other interesting routes for linking risk analytics more closely with macroeconomic models include incorporating default risk and a risk premium into the Mundell-Fleming model to separate out the effects of changes in interest rates resulting from changes in the market for liquidity and from changes in the risk premium on debt (see Gray and Malone, 2009).

at the start of the implementation of fully-fledged inflation targeting in 2000. An application of it to the design of monetary policy in Chile, using efficiency frontiers, is found in García, Herrera, and Valdés (2002). It is one example of a class of models that can be used for policy analysis in small open economies that, as stated above, are empirically motivated (IS/LM type) and at the same time share many features of the dynamic stochastic, micro-founded, general equilibrium models used by central banks.[19]

2.1.1 The equation for the output gap

The equation for the output gap is as follows:

$$\begin{aligned} ygap_t = & \beta_1 ygap_{t+1} + \beta_2 ygap_{t-1} + \beta_3 ygap_{t-2} + \beta_4 ygap_{t-3} + \beta_5 (r_{t-1}) \\ & + \beta_6 (rl_{t-2}) + \beta_7 (q_{t-4}) + \beta_8 (dtd_t) + \varepsilon_t^y , \end{aligned} \tag{1}$$

where *ygap* corresponds to the output gap (that is, the log deviation of GDP with respect to its trend), *r* is the short-run real interest rate, *rl* is the long-run real interest rate, *q* is the real exchange rate, and *dtd* is distance to default, which is also modeled here. As was explained in detail above, *dtd* is a financial risk indicator that could reflect, in general, the financial conditions that the economy faces. Finally, ε_t^y is a shock to GDP. All variables are expressed as log deviations from steady state.

2.1.2 The Phillips curve

The Phillips curve equation is

$$\begin{aligned} \Delta\pi_t = & \alpha_1 \left[(\pi_{t+1}^e + \pi_t)/2 - \pi_{t-1} \right] + \alpha_2 \left[(\pi_{t-2} + \pi_{t-3} + \pi_{t-4})/3 - \pi_{t-1} \right] \\ & + \alpha_3 \left[(q_{t-1} - q_{t-4})/3 - \pi_{t-1} \right] + \alpha_4 \left[(ygap_{t-1} + ygap_{t-2})/2 \right] + \varepsilon_t^\pi , \end{aligned} \tag{2}$$

where π stands for inflation, π_{t+1}^e represents inflation expectations in the next period, *q* is the real exchange rate, and ε_t^π is a cost-push shock.

19. See Berg, Karam, and Laxton (2006a, p. 3).

2.1.3 The exchange rate equation

The exchange rate equation is equivalent to the interest parity condition:

$$q_t = \delta_1 q_{t+1} + \delta_2 q_{t-1} + (r_t - rf_t) + \delta_3 (dtd_{t-1}) + \varepsilon_t^q. \tag{3}$$

The real exchange rate depends on lags and leads of itself, the domestic policy rate (r), the foreign policy rate (rf), and the risk indicator, which embeds both the sovereign spread for domestic debt and the sovereign spread for foreign debt. According to uncovered interest rate parity, the expected change in the spot exchange rate should be related to the differential between the domestic and foreign interest rates, plus some risk premium.

The long-run interest rate (yield curve) equation describes the relationship between long-run (rl_t) and short-run (r_t) interest rates:

$$(rl_t) = \xi_1 (rl_{t+1}^e) + \xi_2 (rl_{t-1}) + (1 - \xi_1 - \xi_2)(r_t) + \varepsilon_t^{rl}. \tag{4}$$

2.1.4 The reaction function

The reaction function is a Taylor rule:

$$r_t = \rho(r_{t-1}) + (1-\rho)\left\{ rl^{eq} + \theta \begin{bmatrix} \gamma(\pi_{t+1} + \pi_t + \pi_{t-1})/3 \\ +(1-\gamma)(ygap_{t-1}) \end{bmatrix} + \zeta(dtd_t) \right\} + \varepsilon_t^r. \tag{5}$$

The monetary policy interest rate depends on its own lag, the expected inflation gap, the output gap, distance to default, and a policy shock. While including a measure of financial stability in the Taylor rule for setting interest rates may improve efficiency (welfare), especially if financial stability affects output, accurate regulation and supervision of financial institutions could be a better way of targeting financial stability.

2.2 Module 2: Distance-to-Default Model for the Banking System

This module completes the whole system to be simulated simultaneously. The value of assets, A, is derived from the Black-Scholes model,

$$A = \frac{E + B \cdot \exp(-r \cdot t) N(d_2)}{N(d_1)}, \tag{6}$$

where E is the value of equity (or the value of the call option), B is the value of debt in the Black-Scholes model and here also the default barrier, r is the risk-free interest rate, and t is time, which is fixed in the model at one year. Finally, $N(.)$ is the normal cumulative distribution function, and d_1 and d_2 were derived from the Black-Scholes model as described in section 1.1:[20]

$$d_1 = d_2 + \sigma_A \sqrt{t} \tag{7}$$

and

$$d_2 = \frac{\ln(A_0 / B_t) + (r - \sigma_A^2 / 2)t}{\sigma_A \sqrt{t}} + dtd\_shk. \tag{8}$$

Note that d_2 is equal, precisely, to distance to default ($dtd = d_2$).

It is apparent from equation (8) that asset volatility, σ_A, and assets value, A, are crucial for finding dtd. Thus, the system of nonlinear equations requires an equation for σ_A if it is to yield a solution:

$$\sigma_A = \frac{(\sigma_E \cdot E)}{\left[A \cdot N(d_1)\right]}, \tag{9}$$

where, σ_E stands for volatility of equity.[21]

Bank equity (E) and its volatility (σ_E) were initially set constant, but the results obtained with the model simulations were

20. Dynare has an explicit function built in for the cumulative normal distribution function.

21. Gray and Malone (2008) provide a thorough explanation.

counterintuitive regarding distance to default. After a cost-push shock hit the economy, inflation went up as expected, GDP fell, and the interest rate increased in reaction to the inflationary pressures. While this negative economic scenario was taking place, distance to default was growing, signaling a sounder economic situation in the banking industry and among businesses in general, which is not a sensible outcome. The efficiency frontiers obtained were not satisfactory, either. By the same token, after a positive shock to GDP, which was accompanied by an interest rate hike, distance to default fell as if the economy were more vulnerable. This is so because in the model, higher interest rates have a negative effect on the level of assets, even if the economy is in better shape.

We therefore adopted a new strategy of modeling both E and its volatility, σ_E. As mentioned earlier, distance to default affects the macroeconomic variables in several ways: namely, by affecting GDP, the real exchange rate, and the interest rate in equations (1), (3), and (5) of the macroeconomic model, respectively. In the following equations, GDP affects banks' capital, E, and its volatility, σ_E. It also affects distance to default through this channel, making the whole system of equations completely endogenous. Another channel of endogeneity is the effect of interest rate on assets, A, and on the volatility of equity, σ_E:[22]

$$E_t = \rho E_{t-1} + 0.01 \cdot ygap_t; \tag{10}$$

$$\sigma_E = 0.1 + 3 \cdot (r_t) - (ygap_{t+1} + ygap_t + ygap_{t-4})/3. \tag{11}$$

The parameters of the macroeconomic model (see table 1) were estimated for carrying out monetary policy analysis. Although, as we said above, this is mostly a theoretical exercise in which some of the model parameters were calibrated either in the yield curve (ξ) or in the reaction function (θ, γ, and ζ), and the parameters related to distance to default were calibrated in the interest parity condition and the Phillips curve, which are used in the sensitivity analysis of the next section.

22. The spread put is an alternative measure of risk. It is described in Gray, Merton, and Bodie (2008) and Gray and Malone (2008) as a function of the value of the put option, the default barrier, the risk free rate, and time: $spread\_put = -1/t \cdot \log[1 - \text{PUT}/\text{BB} \cdot \exp(-r \cdot t)] - 0.00925382$. Although the spread put is a useful concept, it was not used in the simulations performed with the model here.

Table 1. Parameters of the Macroeconomic Model

Parameter	*Parameter*
$\beta_1 = 0.1$	$\alpha_3 = 0.05$
$\beta_2 = -0.1$	$\alpha_4 = 0.15$
$\beta_3 = -0.6$	$\delta_1 = 0.3$
$\beta_4 = -0.4$	$\delta_2 = 0.6$
$\beta_5 = -0.5$	$\delta_3 = -0.04$
$\beta_6 = -0.5$	$\xi_1 = 0.5$
$\beta_7 = 0.02$	$\xi_2 = 0.45$
$\beta_8 = 0.2$	$\rho = 0.8$
$\alpha_1 = 0.3$	$\theta = 1.3$
$\alpha_2 = 0.5$	$\gamma = 0.2, 0.3, \ldots, 1.2$
$\alpha_3 = 0.05$	$\zeta = 0.5, 1.0, 1.5$

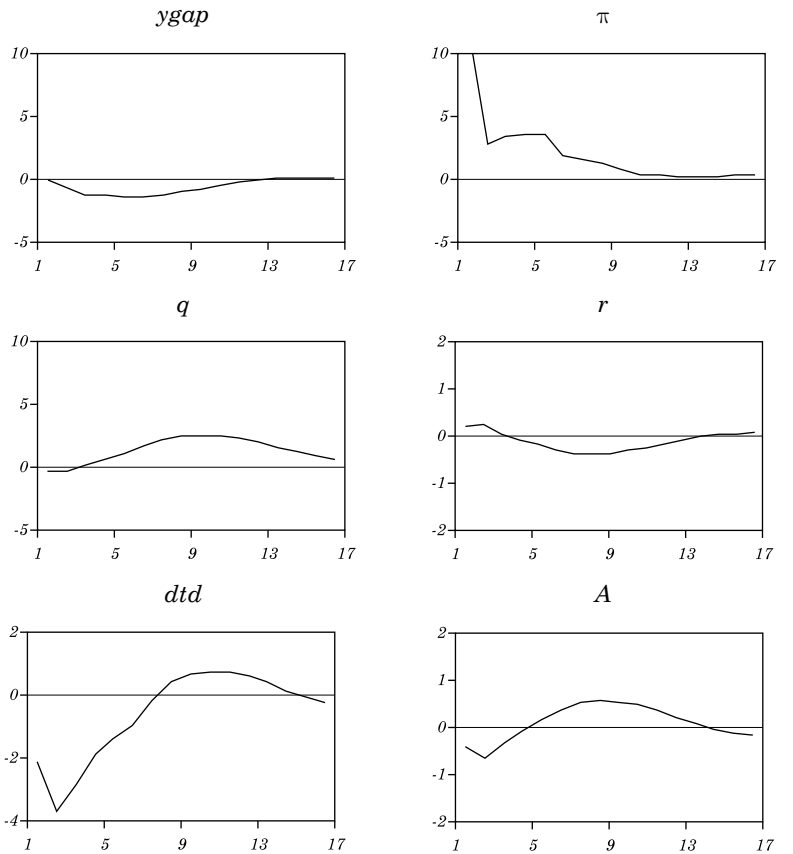
Source: Authors' calculations.

3. Stochastic Simulations and Policy Analysis

To understand how the model works, we first obtained impulse responses (figure 4). We then assess different monetary policy alternatives and model calibrations by building efficiency frontiers with the volatilities of GDP and inflation (García, Herrera, and Valdés, 2002; Laxton and Pesenti, 2003). Specifically, we measure the responses of GDP, inflation, the exchange rate, the monetary policy interest rate, *r*, the CCA-derived risk indicator, *dtd*, and assets following a shock of 100 basis points to GDP and inflation.

Output falls after an inflation shock (cost-push shock) hits the economy, taking the output gap (*ygap*) to negative levels. In contrast, the interest rate tends to increase initially; when combined with the output gap reduction, this increases financial vulnerability and reduces the distance to default significantly (figure 4). The drop in the distance to default is so large that an otherwise increasing interest rate ends up falling while the exchange rate increases. This is so because the exchange rate is not only affected by the interest rate, but also by *dtd* through the risk premium.

Figure 4. Responses to a cost-push shock to inflation (π)

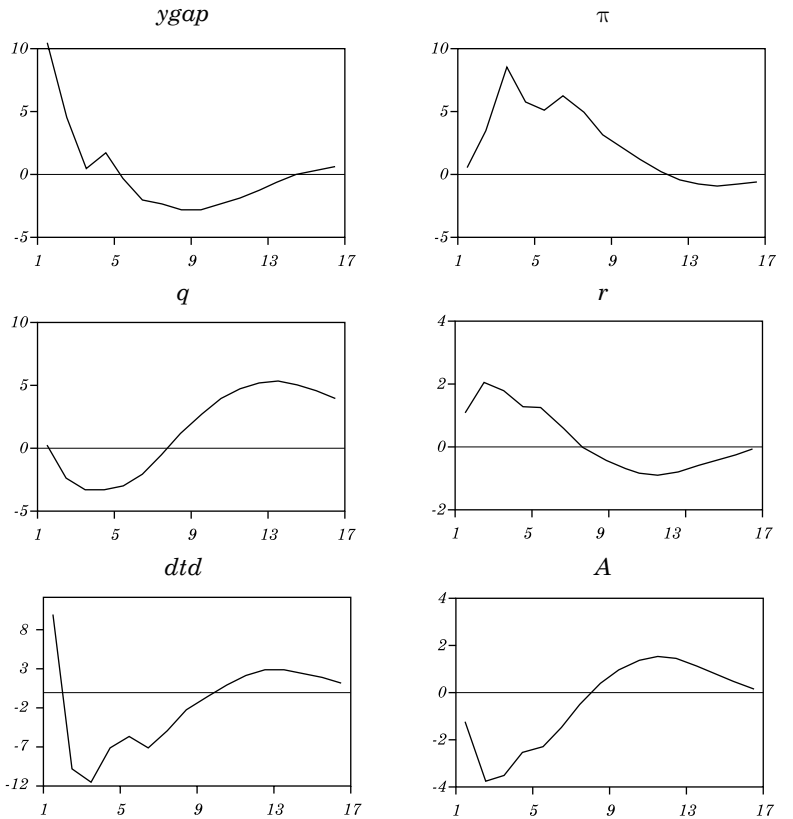


Source: Authors' calculations.

A positive shock to the output gap, in turn, causes GDP and inflation to increase. Interest rates also increase, while the exchange rate falls in line with economic intuition. The system takes around four years to return to equilibrium after the shock (figure 5).[23]

23. A negative shock to distance to default (not reported) causes an initial small drop in *ygap,* but since *dtd* is included in the policy reaction function, the original shock is followed by a reduction in the monetary policy rate. Moreover, arbitrage through the uncovered interest parity and the respective hike of the risk premium result in a large real depreciation. Thus, the interest rate and the exchange rate fuel a GDP expansion.

Figure 5. Responses to a shock to GDP (*y*)



Source: Authors' calculations.

In general, the model works as expected according to standard economic intuition. There is strong interaction among macroeconomic variables, and *dtd* has a large impact on the monetary policy rate, the real exchange rate, and even the output gap.

The efficiency frontiers are built combining the volatility of inflation and GDP that results after the economy is hit repeatedly by shocks drawn from a normal distribution. Using Dynare, we simulated the artificial economy for 200 periods, repeatedly, and computed the average standard deviations of the variables between periods 100 and 120 across the repetitions. The purpose of the exercise is to compare frontiers that were obtained with a combination of ten weights, in the policy rule, for both the inflation

and the output gap objectives, respectively, using three different weights on distance to default.[24] Additional frontiers are obtained using a similar procedure but changing one of the parameters of the model. Whenever a frontier is closer to the origin, the volatility tradeoff is smaller, and it is possible to say that the policy choice is better for the central bank and the society as a whole.

Figures 6 through 9 all include three frontiers, which were obtained with a traditional Taylor rule that includes *dtd* in addition to inflation and GDP gaps ($\theta = 0.5$, $\rho = 0.6$, and $\gamma = 0.6$). The first line results from a rule in which *dtd* has a small weight (with a coefficient $\zeta = 0.5$); that is, authorities react only weakly to the risk indicator (dotted line). The other lines in the figures correspond to alternative reaction functions for monetary policy that have a larger weight of *dtd*, with coefficients ζ equal to 1.0 and 1.5, respectively (dashed and solid lines). In summary, besides reacting to inflation and GDP gaps, the monetary authority also reacts to distance to default, increasing the interest rate when *dtd* is large, but reducing it when the banking system is close to default by more than is warranted by the inflation and output gaps alone. This is so because negative shocks to asset prices and liquidity could end up in credit risk crises, with systemic consequences for lending and production. On the other side, a very large *dtd* could be the result of asset bubbles, which are usually associated with financial turmoil when they burst.

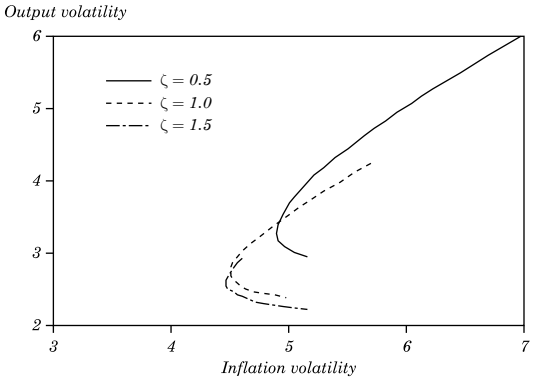
3.1 Reaction Size to *dtd* in the Policy Rule

The size of the reaction to *dtd* in the Taylor rule has a very significant effect on the results. Indeed, the larger the coefficient associated with *dtd* in the authorities' reaction function, the closer to the origin is the frontier obtained with the simulations (solid line in figure 6). Therefore, the central bank's stabilization of *dtd* contributes to stabilizing the volatilities of both GDP and inflation, which fall more with a larger coefficient on *dtd* but with diminishing marginal gains. Increasing the coefficient from 0.5 to 1.0 generates

24. The combination of coefficients on inflation and output starts with 1.2 and 0.1, respectively. To get the second combination, the coefficient on inflation declines, while the weight on output gap increases—both by 0.1 each time. Therefore, another point for the volatility of inflation and output would be obtained with the combination of 1.1 and 0.2 weights in the monetary policy rule. A third one would be 1.0 and 0.3 and so on, up to ten combinations.

a large reduction in the volatility of GDP and inflation, while using a coefficient of 1.5 improves the trade-off only marginally.

Figure 6. Efficiency frontiers



Source: Authors' calculations.

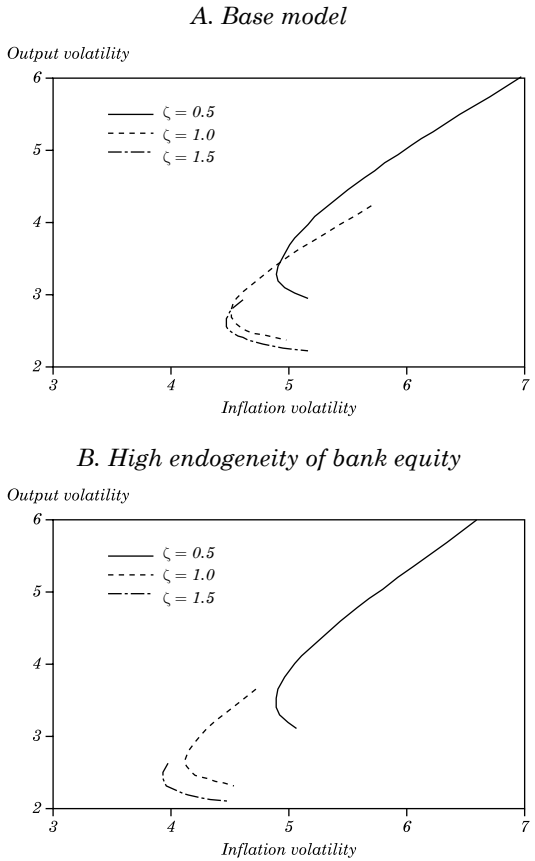
3.2 Endogenous Effect on Bank Equity (E) and Its Volatility (σ_E)

This experiment consists of substantially increasing the effect of GDP on both bank equity and its volatility. This is implemented by augmenting the coefficient of *ygap* from 0.01 to 0.10 in equation (10) and from 1.0 to 1.5 in equation (11). If the feedback from GDP to bank equity and *dtd* (endogeneity) is stronger, the gains by reacting strongly to *dtd* are even larger than in the base model (figure 7). In fact, a comparison of the two panels in the figure shows that the volatility reduction of both variables, included in the frontier, is much larger here than in the base model.

3.3 Effect of *dtd* on the Real Exchange Rate

In this experiment the effect (coefficient) of *dtd* in the (risk premium) exchange rate equation (3) was increased from 0.04 to 0.50 (figure 8, panel B). Again, the solid line, which represents the frontier obtained with a larger weight on *dtd* in the reaction function, includes points that are closer to the origin than any

Figure 7. Efficiency Frontiers and the Endogeneity of Bank Equity

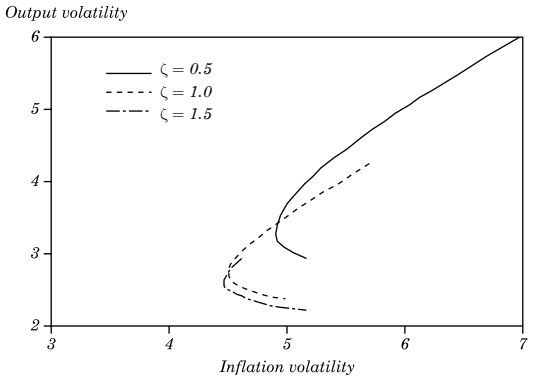


Source: Authors' calculations.

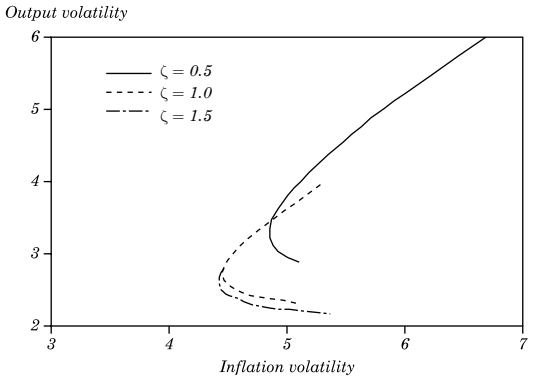
point in the dashed or dotted lines. Thus, this policy should be preferred by the central bank. The gains in terms of volatility are very similar in both panels of figure 8, although panel B only shows small differences with respect to the baseline model. The shape of the frontiers obtained in this experiment indicates that putting more weight on inflation generates a larger reduction in inflation volatility.

Figure 8. Efficiency Frontiers and the Interest Parity Condition

A. Base model



B. High effect of dtd on the real exchange rate



Source: Authors' calculations.

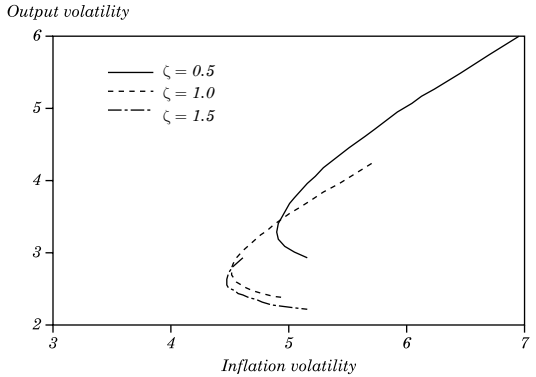
3.4 Higher Pass-through

Were the pass-though from exchange rate to inflation larger (0.7 instead of 0.05), the central bank policy would be more efficient if it reacted to *dtd*. Indeed, by reacting to *dtd* the central bank is able to reduce volatility mostly of output. As shown in figure 9, the frontiers move downward whenever the coefficient associated with *dtd,* in the monetary policy rule, increases. A high level of pass-through is an important issue in very open economies. If prices are very flexible

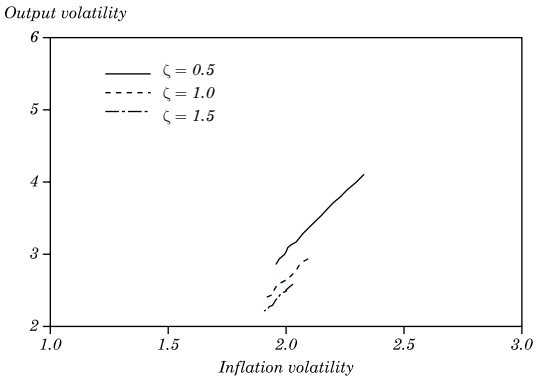
and quickly reflect any movement of the exchange rate, it would be more difficult for relative prices to adjust after a shock, which could make GDP more volatile too.

Figure 9. Efficiency Frontiers and Pass-through

A. Base model



B. Higher pass-through



Source: Authors' calculations.

3.5 Summary

The simulations of the macroeconomic model show that it is more efficient for the central bank to put a larger weight on *dtd* in the reaction function, given that inflation and output volatility decrease. Whenever pass-through from the exchange rate to prices is very high,

including *dtd* in the reaction function will reduce output volatility without increasing the variability of inflation. In addition, whether financial vulnerability or *dtd* has a larger impact on the exchange rate, or GDP has a larger effect on bank equity and, through it, on *dtd* (that is, endogeneity is high), it is more efficient to include *dtd* in the reaction function because the central bank is then able to reduce the volatility of both inflation and output.

4. Conclusions

The main objective of this article was the integration of the analysis of financial sector vulnerability into macroeconomic models, which is an area of important and growing interest for policymakers in both developed and emerging markets. This paper uses contingent claims analysis tools, developed in finance, to construct financial stability indicators in a standard monetary policy model. Financial sector risk affects the economy, while the economy (GDP) and interest rates affect financial sector credit risk.

The new framework is simple, but powerful for monetary policy analysis. The model incorporates the main variables analyzed by policymakers, but it is small enough to facilitate understanding how it works. Although the system stochastically simulates an artificial economy, the empirical evidence supports the model. In addition, impulse responses behave in accordance with economic intuition.

The main question to be answered with the integrated model was whether or not the central bank should explicitly include the financial stability indicator in the interest rate reaction function. The alternative is to react only indirectly to financial risk by reacting to inflation and GDP gaps, since they already include the effect of financial factors on the economy. To reach the objective, efficiency frontiers were built with the volatility of inflation and output obtained from stochastic simulations. In general, we find that including the distance to default (*dtd*) in the reaction function reduces both inflation and output volatility. Moving the policy interest rate more than what is consistent with the inflation and output gaps is efficient because negative shocks to asset prices and liquidity could lead to credit risk crises, with negative systemic consequences on the financial system and GDP.

We also performed a set of exercises in which some of the model parameters were calibrated to reflect and assess actual differences among economies regarding exchange rate pass-through,

the relation between financial risk and exchange rate through the parity condition (risk premium), and the endogeneity of the financial indicator, namely, the degree in which the macroeconomic variables (GDP and interest rates) affect distance to default through bank assets, bank equity, and equity volatility. Whenever the pass-through from the exchange rate to inflation is higher, when the impact of financial vulnerability (*dtd*) on the exchange rate is larger, and when the effect of GDP on bank equity (endogeneity) is stronger, it is more efficient to include *dtd* in the reaction function, with a large coefficient. Finally, this is a first approximation to the subject, and considerable refinements and extensions could be introduced in the future. A non-exhaustive list includes the following: the use of other financial sector risk indicators; the inclusion of combinations of financial scenarios (strong, normal, fragile); adjustments to the dynamics of the macroeconomic model; the adoption of a more micro-founded general equilibrium macroeconomic model; and the introduction of empirical evidence for other countries or the application of the framework to other economies. All these extensions are left for future research.

Appendix A
Extensions of the Merton Model

Numerous extensions of the original Merton model have been developed by relaxing some of its assumptions. Restrictions of the model include the following assumptions: (i) default can occur only at the maturity date of the debt; (ii) there is a fixed default barrier; (iii) there is a constant risk-free rate; and, (iv) asset volatility is constant. Cossin and Pirotte (2001) provide a good summary of extensions of the Merton model. Black and Cox (1976) extended the Merton model to relax assumptions (i) and (ii) above by introducing a "first passage time" model in which default can occur prior to the maturity of the debt if the asset falls below a specified barrier function for the first time.

Although the strict theoretical condition in the Merton model for default is that the value of assets is less than the required payments due on the debt, in the real world default typically occurs at much higher asset values, either because of a material breach of a debt covenant or because assets cannot be sold to meet the payments (that is, inadequate liquidity) or because the sovereign decides to default and induce a debt renegotiation rather than sell assets. To capture these real-world conditions for default in the model, we specify a market value of total assets at which default occurs. We call this level of assets that trigger default the distress barrier. This barrier can be viewed as the present value of the promised payments discounted at the risk-free rate. The approach used in the KMV model sets the barrier level equal to the sum of the book value of short-term debt, promised interest payments for the next 12 months, and half of long-term debt (see Crouhy, Galai, and Mark, 2000; Crosbie, 1999, 2001).

In the 1990s, the KMV model was based on the Vasicek and Kealhofer model, which has multiple layers of liabilities and several confidential features. The Moody's KMV expected default frequency (EDF) credit measure is calculated using an iterative procedure to solve for asset volatility. This distance to default was then mapped to actual default probabilities using a database of detailed real-world default probabilities for many firms. The Moody's KMV distance to default and the cumulative expected default probabilities (CEDF) are calculated as follows:

$$DD_{KMV} = f\left[\frac{\ln(A_0 / B_t) + (\mu_A - \sigma_A^2 / 2)t}{\sigma_A \sqrt{t}}\right];$$

$$CEDF_t = f\left[DD_{KMV}(t)\right].$$

This definition of DD_{KMV} includes the real drift of the asset, μ_A, whereas the distance to default from the Merton approach has r for the asset drift. Since Moody's KMV estimates the actual default probabilities, the risk-neutral default probabilities are calculated from the correlation of the implied asset with the market, the market Sharpe ratio, and the time horizon.

The Merton model has been extended to include stochastic interest rates, as well. Shimko, Tejima, and Van Deventer (1993) include a Vasicek interest rate term structure model that relaxes assumption (iii) above, allowing the risk-free interest rate to change and including the correlation of asset return with the interest rate. There are two stochastic factors: the asset and the interest rate. This model is frequently called the STV model. Longstaff and Schwartz (1995) take the Black and Cox (1976) model and add in stochastic interest rates, similar to the way STV includes interest rates.

The CreditGrades model (Finger, 2002) includes a diffusion of a firm's assets and a first passage time default with a stochastic default barrier. The model was modified to incorporate equity derivatives (Stamicar and Finger, 2005). Recent research studies the relationship between the volatility skew implied by equity options and CDS spreads (Hull et. al. 2004). They establish a relationship between the implied volatility of two equity options, leverage and asset volatility. This approach is, in fact, another way of implementing Merton's model to get spreads and risk-neutral default probabilities directly from the implied volatility of equity options. Zou (2003) presents a similar approach using several equity options.

Financial support for liquidity and potential credit risk from the authorities is likely to be provided before the default barrier is reached. A minimum capital barrier, or simply a capital barrier, can be defined in addition to the default barrier. For instance, the default barrier plus 8 percent of the market value of assets could be used as the minimum 8 percent capital barrier. The area between the minimum capital barrier and the default barrier represents the probability of falling below minimum capital but not as far as default. The value of this area is calculated as the implicit put option below the minimum capital barrier minus the implicit default put option. We call the value of the area the capital barrier put option or capital barrier expected loss. This is particularly relevant to the

central bank, as it is a measure of loss directly related to the liquidity support and financial support that would be needed to get the bank asset level above the minimum capital level.

Finally, contingent claims models can be used to assess systemic risk in portfolios of financial institutions, including the correlation or dependence structure among them.

Appendix B

Regression Results of Output and the Output Gap on the Distance to Default of the Banking System

The first regression is on GDP growth:

$$\Delta y_t = a + \alpha_1 r_{t-1} + \alpha_2 \Delta dtd_{t-1} + \alpha_3 \Delta e_{t-1} + \alpha_4 \Delta y_{t-1} + \varepsilon_t.$$

The results are presented in table B1. The second is a regression on the output gap:

$$ygap_t = c + \alpha_1 \Delta dtd_{t-1} + \alpha_2 \Delta e_{t-3} + \alpha_3 ygap_{t-1} + \alpha_4 ygap_{t-3} + \xi_t.$$

The results are presented in B2. These regressions show that changes in *dtd* are significant in explaining both quarterly GDP growth (the first equation) and the output gap (the second equation) with the expected positive sign.

Table B1. GDP Growth Regressions[a]

Variable	*Coefficient*	*Standard error*	*t statistic*	*Probability*
Constant	0.011	0.002	4.830	0.000
r_{t-1}	–0.001	0.000	–3.723	0.000
Δe_{t-1}	0.046	0.019	2.438	0.017
Δdtd_{t-1}	0.012	0.003	3.551	0.001
Δy_{t-1}	0.463	0.074	6.283	0.000
Summary statistic				
R-squared	0.574	Log likelihood		358.890
Adjusted *R*-squared	0.557	Akaike information criterion		–6.677
Durbin-Watson statistic	1.912	Schwarz criterion		–6.552

Source: Authors' calculations.
a. The dependent variable is Δy_t. The adjusted sample covers the period from May 1998 to February 2007 and includes 106 observations (after adjustments).

Table B2. Output Gap Regressions[a]

Variable	*Coefficient*	*Standard error*	*t statistic*	*Probability*
Constant	–1.736	0.470	–3.691	0.000
Δe_{t-3}	4.134	1.639	2.522	0.013
Δdtd_{t-1}	0.934	0.256	3.653	0.000
$ygap_{t-1}$	0.513	0.082	6.275	0.000
$ygap_{t-3}$	0.225	0.072	3.113	0.002
Summary statistic				
R-squared	0.661	Log likelihood		–115.126
Adjusted R-squared	0.648	Akaike information criterion		2.204
Durbin-Watson statistic	1.842	Schwarz criterion		2.328

Source: Authors' calculations.
a. The dependent variable is $ygap_t$. The adjusted sample covers the period from February 1998 to February 2007 and includes 109 observations (after adjustments).

Appendix C
Extensions and Further Applications

The central bank may expand its set of policy instruments to better accommodate its multiple objectives. Additional tools that can be used to target financial stability include the reserve requirements for banks and other measures of capital adequacy, such as the value-at-risk-based measures advocated in Basel II. A rule can be specified for targeting such a measure of capital adequacy, C, as follows:

$$C_t = \phi_1 C_{t-1} + (1 - \phi_1)(\eta_2 ygap_t + \eta_3 fsigap_t) + \varepsilon_{10,t}.$$

The closer the parameter ϕ_1 is to one, the more continuity is built into the capital adequacy requirement. As in the case of interest rates, some continuity is important, because significant changes in capital adequacy requirements, or interest rates, in a short amount of time can also potentially contribute to instability, as banks move en masse to comply with the new requirements. The second term in the above rule, which is multiplied by the coefficient $1 - \phi_1$, allows the central bank to use capital adequacy requirements, or other variables that affect the risk profile of the banking sector, to respond to deviations of inflation, output, and financial stability from their targets.[25] Because lower capital adequacy requirements stimulate lending, they may be able to contribute to higher investment that stimulates output when output is below the target. Likewise, more stringent capital adequacy requirements can help increase the financial stability indicator when it is below the target, by lowering the probability of banking sector instability or widespread defaults. Finally, the sovereign and the central bank will choose the coefficients of their decisions rules to maximize their objective functions.

25. See Gray and Malone (2008) for details.

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Equity Market Spillovers in the Americas

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Many aspects of financial markets merit monitoring in risk management and portfolio allocation contexts, including (and perhaps especially) in contexts of interest to central banks. Much recent attention, for example, has been devoted to measuring and forecasting return volatilities and correlations, as in the case of market-based implied volatilities. One can extend the market-based approach by monitoring not implied volatility extracted from a single option, but rather entire risk-neutral densities extracted from sets of options with different strike prices (Gray and Malone, 2008). This is consistent with the density forecasting perspective on risk measurement advocated by Diebold, Gunther, and Tay (1998) and several of the references therein.

In many contexts, however, derivatives markets are not available for the objects of interest. Such is the case in this paper, in which we focus on measuring spillovers in equity returns and equity return volatilities. In particular, we consider cross-country stock market spillovers in the Americas, asking how much of the forecast error variance of a country's broad stock market return (or volatility) is due to shocks in other countries' markets. There are simply no derivatives markets from which one might obtain "implied spillovers."

We thank the Central Bank of Chile for motivating us to pursue this research and Dimitrios Tsomocos for providing constructive comments on its progress. We are especially grateful to the conference organizers, Rodrigo Alfaro, Dale Gray, and Jorge Selaive. For comments at earlier stages of the research program of which this paper is a part, we thank Jon Faust, Roberto Rigobon, and Harald Uhlig. For research support, we thank the National Science Foundation.

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We therefore use a non-market-based spillover estimator, which turns out to be quite effective. It is widely applicable, simple, and intuitive, yet also rigorous and replicable. It facilitates the study of both crisis and noncrisis episodes, including trends and cycles (and bursts) in spillovers. Finally, although it conveys useful information, it nevertheless sidesteps the contentious issues associated with the definition and existence of episodes of contagion or herd behavior.[1]

We proceed as follows. In section 1 we motivate and describe our measure of spillovers, which is based on the variance decomposition of a vector autoregression. In section 2 we use our spillover measure to assess stock market spillovers in the Americas in recent decades, focusing on both return and volatility spillovers. In section 3 we summarize our work and sketch directions for future research.

1. Measuring Spillovers

This section describes a spillover index proposed in an earlier work (Diebold and Yilmaz, 2009), which we then use to measure spillovers in the Americas. The index is quite general and flexible, based directly on variance decompositions from vector autoregressions (VARs) fitted to returns or volatilities. It contrasts with approaches such as Edwards and Susmel (2001), which produce only a binary indicator of a high or low state (our index varies continuously) and which are econometrically tractable only for small numbers of countries (our index is simple to calculate even for large numbers of countries).

The basic spillover index follows directly from the familiar notion of a variance decomposition associated with an N-variable VAR. Roughly, for each asset i we simply add the shares of its forecast error variance coming from shocks to asset j, for all $j \neq i$, and then we add across all $i = 1,\ldots,N$.

To minimize notational clutter, consider first the simple example of a covariance stationary first-order two-variable VAR,

$$\mathbf{x}_t = \mathbf{\Phi}\mathbf{x}_{t-1} + \varepsilon_t,$$

where $\mathbf{x}_t = (x_{1,t}, x_{2,t})'$ and $\mathbf{\Phi}$ is a 2 x 2 parameter matrix. In our subsequent empirical work, $\mathbf{x}_t$ is either a vector of stock returns or

1. On contagion (or lack thereof), see, for example, Edwards and Rigobon (2002) and Forbes and Rigobon (2002).

a vector of stock return volatilities. By covariance stationarity, the moving average representation of the VAR exists and is given by

$$\mathbf{x}_t = \mathbf{\Theta}(L)\varepsilon_t,$$

where $\mathbf{\Theta}(L) = (\mathbf{I} - \mathbf{\Phi}L)^{-1}$. It will prove useful to rewrite the moving average representation as

$$\mathbf{x}_t = \mathbf{A}(L)\mathbf{u}_t,$$

where $\mathbf{A}(L) = \mathbf{\Theta}(L)\mathbf{Q}_t^{-1}$, $\mathbf{u}_t = \mathbf{Q}_t\varepsilon_t$, $E(\mathbf{u}_t\mathbf{u}_t') = \mathbf{I}$ and $\mathbf{Q}_t^{-1}$ is the unique lower-triangular Cholesky factor of the covariance matrix of ε_t.

Now consider one-step-ahead forecasting. Immediately, the optimal forecast (more precisely, the Wiener-Kolmogorov linear least-squares forecast) is

$$\mathbf{x}_{t+1,t} = \mathbf{\Phi}\mathbf{x}_t,$$

with corresponding one-step-ahead error vector

$$\mathbf{e}_{t+1,t} = \mathbf{x}_{t+1} - \mathbf{x}_{t+1,t} = \mathbf{A}_0\mathbf{u}_{t+1} = \begin{bmatrix} a_{0,11} & a_{0,12} \\ a_{0,21} & a_{0,22} \end{bmatrix} \begin{bmatrix} u_{1,t+1} \\ u_{2,t+1} \end{bmatrix},$$

which has covariance matrix

$$E(\mathbf{e}_{t+1,t}\mathbf{e}_{t+1,t}') = \mathbf{A}_0\mathbf{A}_0'.$$

Hence, in particular, the variance of the one-step-ahead error in forecasting $\mathbf{x}_{1,t}$ is $a_{0,11}^2 + a_{0,12}^2$, and the variance of the one-step-ahead error in forecasting $\mathbf{x}_{2,t}$ is $a_{0,21}^2 + a_{0,22}^2$.

Variance decompositions allow us to split the forecast error variances of each variable into parts attributable to the various system shocks. More precisely, for the example at hand, they answer the following questions. What fraction of the one-step-ahead error variance in forecasting x_1 is due to shocks to x_1 and what fraction is due to shocks to x_2? And similarly, what fraction of the one-step-ahead error variance in forecasting x_2 is due to shocks to x_1 versus shocks to x_2?

Let us define own-variance shares to be the fractions of the one-step-ahead error variances in forecasting x_i due to shocks to x_i, for $i = 1, 2$,

and cross-variance shares, or spillovers, to be the fractions of the one-step-ahead error variances in forecasting x_i due to shocks to x_j, for $i, j = 1, 2, i \neq j$. There are two possible spillovers in our simple two-variable example: $x_{1,t}$ shocks that affect the forecast error variance of $x_{2,t}$, with relative contribution $\tilde{a}^2_{0,21} = [a^2_{0,21} / (a^2_{0,21} + a^2_{0,22})]$, and $x_{2,t}$ shocks that affect the forecast error variance of x_{1t}, with relative contribution $\tilde{a}^2_{0,12} = [a^2_{0,12} / (a^2_{0,11} + a^2_{0,12})]$. Hence the total spillover is given by $\tilde{a}^2_{0,12} + \tilde{a}^2_{0,21} = [a^2_{0,12} / (a^2_{0,11} + a^2_{0,12})] + [a^2_{0,21} / (a^2_{0,21} + a^2_{0,22})]$. We can convert the total spillover to an easily interpreted index by expressing it as a ratio of the sum of relative contributions to the forecast error variance, which is $(\tilde{a}^2_{0,11} + \tilde{a}^2_{0,12}) + (\tilde{a}^2_{0,21} + \tilde{a}^2_{0,22}) = 2$. With the ratio expressed as a percent, the spillover index is

$$S = \frac{\tilde{a}^2_{0,12} + \tilde{a}^2_{0,21}}{2} \cdot 100.$$

Having illustrated the spillover index in a simple first-order two-variable case, it is a simple matter to generalize it to richer dynamic environments. In particular, for a pth-order N-variable VAR (but still using one-step-ahead forecasts), we immediately have

$$S = \frac{\sum_{i,j=1, i \neq j}^{N} \tilde{a}^2_{0,ij}}{N} \cdot 100.$$

For the fully general case of a pth-order N-variable VAR, using h-step-ahead forecasts, we have

$$S = \frac{\sum_{k=0}^{h-1} \sum_{i,j=1, i \neq j}^{N} \tilde{a}^2_{k,ij}}{N} \cdot 100.$$

The generality of our spillover measure is often useful, and we exploit it in our subsequent empirical analysis of return and volatility spillovers in the Americas.[2]

2. Although it is beyond the scope of this paper, future work could profitably explore the relationship of our spillover measure to others based, for example, on time-varying covariances or correlations.

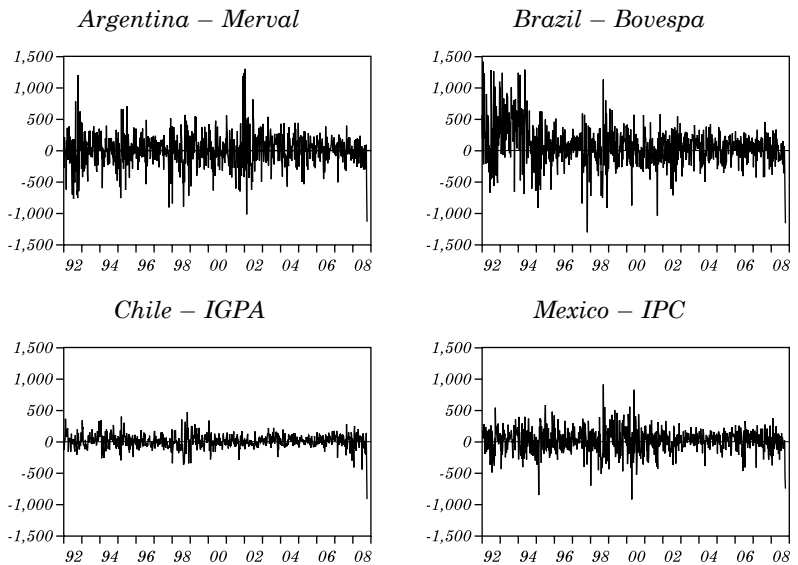
2. Empirical Analysis of Stock Market Spillovers in the Americas

Here we examine stock market spillovers in the Americas, focusing on both return and volatility spillovers.

2.1 Data

We examine broad stock market returns from 1 January 1992 through 10 October 2008 in four South American countries: Argentina (Merval), Brazil (Bovespa), Chile (IGPA), and Mexico (IPC). We measure returns weekly, using underlying stock index levels at the Friday close, and we express them as annualized percentages. The annualized weekly percent return for market i is $r_{it} = 52 \cdot 100 \cdot (\Delta \ln P_{it})$. We plot the four countries' returns in figure 1, and we provide summary statistics in table 1.

Figure 1. South American Stock Market Returns



Source: Authors' computations.

Table 1. Summary Statistics: South American Stock Market Returns

Statistic	*Argentina*	*Brazil*	*Chile*	*Mexico*
Mean	2.49	64.33	8.50	15.75
Median	19.75	55.04	8.74	28.82
Maximum	1,301.99	1,417.96	473.78	910.16
Minimum	−1,135.39	−1,303.04	−915.84	−921.24
Standard deviation	264.78	317.84	111.77	188.51
Skewness	−0.02	0.39	−0.70	−0.32
Kurtosis	5.79	5.70	9.60	5.36
Jarque-Bera	283.40	287.63	1,661.05	217.78
Probability	0.00	0.00	0.00	0.00
No. observations	875	875	875	875

Source: Authors' computations.

We also measure return volatilities (standard deviations) weekly. In the tradition of Garman and Klass (1980), we estimate weekly return volatilities using weekly high, low, opening, and closing prices obtained from underlying daily high, low, opening, and closing data, from the Monday open to the Friday close:[3]

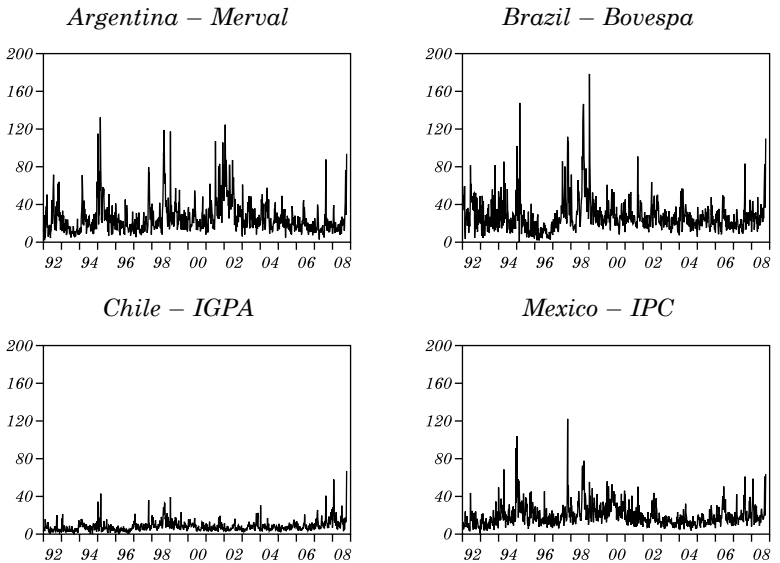
$$\tilde{\sigma}_{it}^2 = 0.511(H_{it} - L_{it})^2 - 0.019\begin{bmatrix}(C_{it} - O_{it})(H_{it} + L_{it} - 2O_{it}) \\ -2(H_{it} - O_{it})(L_{it} - O_{it})\end{bmatrix}$$
$$-0.383(C_{it} - O_{it})^2,$$

where H is the Monday–Friday high, L is the Monday–Friday low, O is the Monday opening price, and C is the Friday closing price (all in natural logarithms). Because $\tilde{\sigma}_{it}^2$ is an estimator of the weekly variance, the corresponding estimate of the annualized weekly percent standard deviation (volatility) is $\hat{\sigma}_{it} = 100\sqrt{52 \cdot \tilde{\sigma}_{it}^2}$. We plot the four countries' volatilities in figure 2, and we provide summary statistics in table 2.

Figures and tables 1 and 2 highlight several noteworthy aspects of return and volatility behavior. First, Chilean returns tend to be both

3. See also Parkinson (1980); Alizadeh, Brandt, and Diebold (2002).

Figure 2. South American Stock Market Volatilities



Source: Authors' computations.

Table 2. Summary Statistics: South American Stock Market Volatilities

Statistic	*Argentina*	*Brazil*	*Chile*	*Mexico*
Mean	25.63	27.76	7.97	19.64
Median	20.94	23.88	6.65	16.71
Maximum	132.40	178.58	66.86	122.17
Minimum	1.83	0.08	0.30	0.61
Standard deviation	17.43	18.23	5.85	12.23
Skewness	2.25	2.85	3.50	2.43
Kurtosis	10.12	16.89	25.14	13.97
Jarque-Bera	2,587.20	8,211.40	19,651.30	5,248.50
Probability	0.00	0.00	0.00	0.00
No. observations	875	875	875	875

Source: Authors' computations.

smaller and less variable, on average, than those of the other South American countries. Second, periods of very high volatility typically correspond to financial and economic crises and are typically common across markets. For example, volatility in all stock markets surges during the Mexican tequila crisis of 1995, the East Asian crisis of 1997, the Russian and Brazilian crises of 1998 and 1999, and the global financial crisis of 2007–08.[4]

2.2 Empirical Implementation of the Spillover Measure

We use second-order VARs ($p = 2$), h = ten-step-ahead forecasts, and N = four or five countries (Argentina, Brazil, Chile, and Mexico, with and without the United States). We capture time variation in spillovers by reestimating the VAR weekly, using a hundred-week rolling estimation window. We compute the spillover index only when the parameters of the estimated VAR imply covariance stationarity.

A key issue is identification of the VAR. Traditional orthogonalization using the Cholesky factor of the VAR innovation covariance matrix produces variance decompositions that may depend on ordering. Several partial fixes are available. First, one could attempt a structural identification if credible restrictions on the VAR's innovation covariance matrix could be imposed, but such is usually not the case. Second, building on Faust (1998), one could attempt to bound the range of spillovers corresponding to all $N!$ variance decompositions associated with the set of all possible VAR orderings. Third, building on Pesaran and Shin (1998), one could attempt to make the variance decomposition invariant to ordering.

Finally, one could simply calculate the entire set of spillovers corresponding to all $N!$ variance decompositions associated with the set of all possible VAR orderings. This brute-force approach is unfeasible for large N, but it is preferable when feasible as it involves no auxiliary assumptions. In our case, N is quite small (four or five), so we can straightforwardly calculate and use variance decompositions based on all $N!$ orderings, which we do in most of this paper.

4. The only exception is Argentina's crisis of 2001–02, during which Argentina's surge in volatility was not shared with the other countries.

2.3 South American Spillovers

Tables 3 and 4 present full-sample South American spillover tables for returns and volatilities, respectively.[5] Both return and volatility spillovers are sizable: return spillovers are approximately 19 percent, and volatility spillovers are even larger at 25 percent.

Table 3. Return Spillovers: Full Sample

Country	*Argentina*	*Brazil*	*Chile*	*Mexico*	*Contribution from others*
Argentina	97.63	0.09	0.24	2.04	2.4
Brazil	15.84	83.51	0.01	0.63	16.5
Chile	13.61	8.33	75.57	2.50	24.4
Mexico	22.38	5.77	3.06	68.79	31.2
Contribution to others	51.8	14.2	3.3	5.2	74.5
Contribution incl. own	149.5	97.7	78.9	74.0	Index = 18.6%

Source: Authors' computations.

Table 4. Volatility Spillovers: Full Sample

Country	*Argentina*	*Brazil*	*Chile*	*Mexico*	*Contribution from others*
Argentina	96.00	0.69	1.81	1.51	4.0
Brazil	28.27	67.59	0.60	3.54	32.4
Chile	14.12	14.86	70.98	0.04	29.0
Mexico	18.67	11.36	4.00	65.97	34.0
Contribution to others	61.1	26.9	6.4	5.1	99.5
Contribution incl. own	157.1	94.5	77.4	71.1	Index = 24.9%

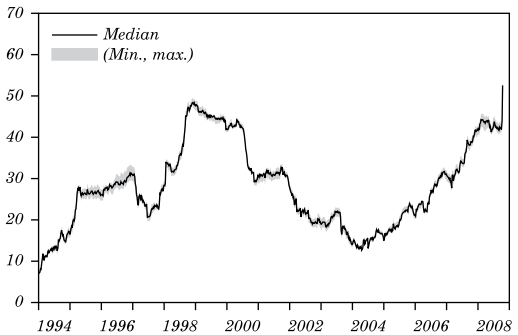
Source: Authors' computations.

One can view tables 3 and 4 as providing measures of spillovers averaged over the full sample. Of greater interest are movements in spillovers over time. Figures 3 and 4 depict dynamic South American

5. The VAR ordering is Argentina, Brazil, Chile, Mexico. Subsequently, we consider all possible orderings.

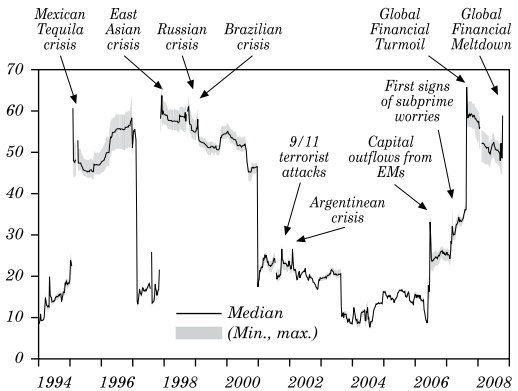
spillover plots for returns and volatilities, respectively, calculated using rolling hundred-week VAR estimation windows. Rather than relying on any particular VAR ordering for Cholesky-factor identification, we calculate the spillover index for every possible VAR ordering. The figures indicate that both return and volatility spillovers vary widely over time and that return spillovers evolve gradually, whereas volatility spillovers show sharper jumps, typically corresponding to crisis events.

Figure 3. Spillover Plot: Returns[a]



Source: Authors' computations.
a. The lines in the figure are medians across all orderings; the gray shaded region gives the range.

Figure 4. Spillover Plot: Volatilities[a]



Source: Authors' computations.
a. The lines in the figure are medians across all orderings; the gray shaded region gives the range.

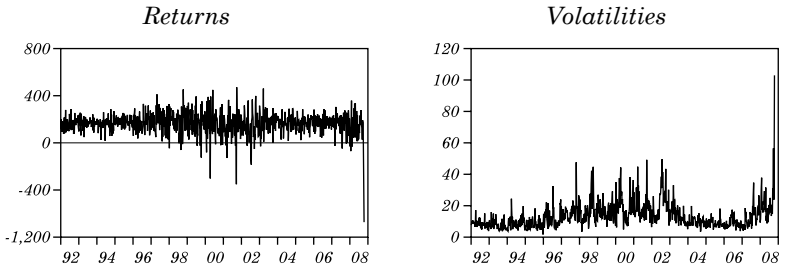
A closer examination of the spillover plots reveals that return spillovers increase as we roll the estimation window through the end of 1994, and they surge to 30 percent immediately after the outbreak of the Mexican tequila crisis in December 1994. Return spillovers drop to 20 percent in late 1996 (as we drop the Mexican crisis from the estimation window), but the Asian and Russian crises keep them from dropping further. Return spillovers peak at nearly 50 percent after the outbreak of the full-fledged Russian crisis in September 1998, and they decline substantially when we drop the Russian crisis from the subsample window. Surprisingly, return spillovers fail to increase during the Brazilian crisis of January 1999. Instead, they continue their secular downward movement, dropping as low as 13 percent in 2004, after which they drift upward, with a jump in the first week of October 2008.

Volatility spillovers, in turn, surge to 50 percent at the outset of the Mexican crisis and fluctuate between 45 and 60 percent before plunging when we drop the crisis from the estimation window. Volatility spillovers again surge during the East Asian crisis of 1997, and they remain high as long as we include the East Asian crisis in the estimation window. Volatility spillovers are also affected by the Russian crisis of September 1998, the Brazilian crisis of January 1999, the 9/11 terrorist attacks in the United States, and the Argentine crisis of January 2002, but only slightly. The largest movements in recent years come from the U.S. subprime crisis and the subsequent global financial meltdown.

2.4 Including the United States

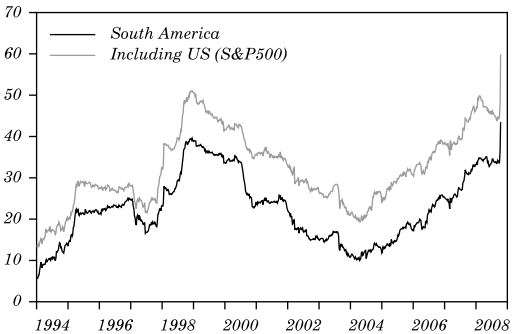
To assess whether the inclusion of the United States affects the spillover results, we include S&P 500 returns and volatilities in the analysis, in addition to the original four South American countries. We plot U.S. returns and volatilities in figure 5 and provide summary statistics in table 5. When the United States is included, return spillovers are always higher and the wedge is roughly the same over time, as shown in figure 6. Volatility spillovers, in contrast, are lower before the Asian crisis and higher afterward, as shown in figure 7.

Figure 5. U.S. Stock Market Returns and Volatilities



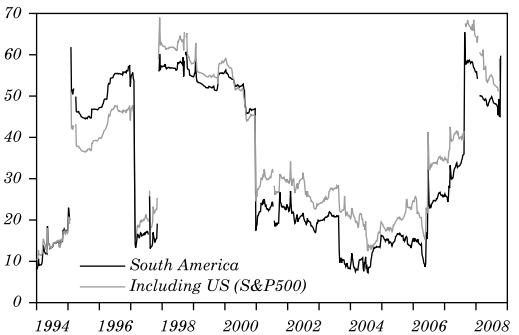
Source: Authors' computations.

Figure 6. Return Spillovers, with and without the United States



Source: Authors' computations.

Figure 7. Volatility Spillovers, with and without the United States



Source: Authors' computations.

Table 5. Summary Statistics: U.S. Stock Market Returns and Volatilities

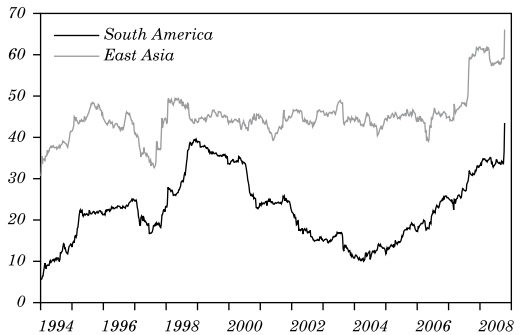
Statistic	*Returns*	*Volatility*
Mean	4.53	13.15
Median	11.97	10.65
Maximum	389.60	102.96
Minimum	−1,044.36	1.54
Standard deviation	115.60	8.22
Skewness	−1.32	2.87
Kurtosis	12.92	21.63
Jarque-Bera	3,845.70	13,850.80
Probability	0.00	0.00
No. observations	875	875

Source: Authors' computations.

2.5 Comparisons to Asian Spillovers

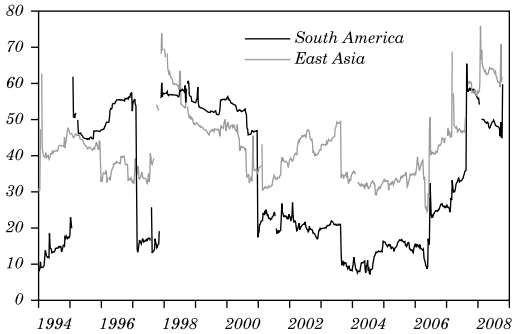
Figures 8 and 9 compare South American return and volatility spillovers to those of ten East Asian countries (namely, Australia, Hong Kong, Indonesia, Japan, Malaysia, Philippines, Singapore, South Korea, Taiwan, and Thailand). The figures demonstrate that South American spillover patterns do not simply track global patterns, although they are not unrelated.

Figure 8. Comparative South American and East Asian Return Spillovers



Source: Authors' computations.

Figure 9. Comparative South American and East Asian Volatility Spillovers



Source: Authors' computations.

South American return spillovers increase substantially during the Mexican, East Asian, and Russian crises, after which they decline continuously until 2004, when they approach the levels of the early 1990s. They increase in 2005 and 2006 during the brief capital outflows from emerging markets in 2006, and they also jump in the first week of October 2008.

East Asian return spillovers, in contrast, are nearly flat from the East Asian crisis until recently. Following the first round of the global financial crisis in July–August of 2007, East Asian return spillovers increase sharply, and they again increase sharply during the financial meltdown in the first week of October 2008.

Return spillovers increase in both South America and East Asia in the early 1990s, but the increase was bigger for South America, especially around the Mexican crisis. Moreover, the Mexican crisis affects South American return spillovers for much longer than East Asian spillovers. Return spillovers increase in both regions during the East Asian crisis, whereas the Russian crisis affects only South America.

Return spillover patterns generally indicate that South American stock markets are not as well integrated as East Asia's. Perhaps the presence of the major Japanese stock market, together with Hong Kong's function as a regional hub, facilitates financial integration and spillovers. Many believe that hub markets play a critical role in spreading shocks, and South America lacks a hub like Hong Kong.

Volatility spillover patterns in South America and East Asia are also quite different. Sometimes they are clearly divergent. For example, during the Mexican crisis South American volatility spillovers jumped from 20 percent to 50 percent, whereas East Asian volatility spillovers were not affected. Other times volatility spillovers move similarly in the two regions. For example, volatility spillovers in both regions respond significantly during both the East Asian crisis and the 2007–08 global liquidity/solvency crisis.

3. Summary and Directions for Future Research

We use the Diebold-Yilmaz (2009) spillover index to assess equity return and volatility spillovers in the Americas. We study both noncrisis and crisis episodes in the 1992–2008 period, including spillover cycles and bursts. Both turn out to be empirically important. In particular, we find striking evidence of divergent behavior in the dynamics of return spillovers and volatility spillovers: return spillovers display gradually evolving cycles but no bursts, whereas volatility spillovers display clear bursts that correspond closely to economic events.

There are several important directions for future research, both substantive and methodological. Substantively, this paper has focused only on cross-country equity market spillovers, but one could also examine within-country (single equity) spillovers, as well as other asset classes and multiple asset classes. In the current environment, for example, spillovers from credit markets to stock markets are of obvious interest. In all cases, moreover, one could also attempt to assess the direction of spillovers, as in Diebold and Yilmaz (2011).

Possible directions for methodological research include enriching (or specializing) the VAR on which the spillover index is based to allow for time-varying coefficients or factor structure, possibly with regime switching as in Diebold and Rudebusch (1996). One could also perform a Bayesian analysis in the framework adopted here or in the extensions sketched above, which could be useful for imposing covariance stationarity.

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Modeling a Housing and Mortgage Crisis

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The current crisis has centered on borrower defaults on mortgages and the associated effects on banks' own credit standing (and in several cases their own default), which in turn led to tightened conditions for lending to new (mortgage) borrowers. Any model that does not incorporate all or most of these key elements cannot possibly hope to capture the defining features of the current crisis. This is particularly true of standard dynamic stochastic general equilibrium (DSGE) models, which (mostly) assume away the possibility of default altogether!

This paper builds on our previous model of a system in which default plays a central role for both borrowers and banks and in which financial intermediation and money thus have a necessary real function. Specifically, we include both an additional good, housing, in the prior composite basket of goods and services and an additional agent, a new entrant to the housing market. Our previous papers on this include Goodhart, Sunirand, and Tsomocos (2004, 2005, 2006).

Dealing with a model with default and heterogeneous agents is not straightforward, which is why standard DSGE models abstract from such concerns despite their resulting lack of realistic micro-foundations. We therefore regard this paper as a preliminary step in a longer exercise. In particular, the shocks that we model in the second period of our two-period model (the first being an initial predetermined

At the time of writing, Alexander P. Vardoulakis was affiliated with the University of Oxford.

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set-up period) can be categorized as supply shocks, in which the agents' endowment declines greatly in the case of adverse shocks. Nevertheless, our model is general enough to allow for the examination of a wide variety of shocks that can lead to financial instability.

In practice, the main adverse shock in 2007–08 was a sharp decline in housing prices in the United States, whereas previously they had been expected to continue rising or, at worst, to hold steady. In a future version of this paper, we will experiment with this and other financial shocks. The main reason for proceeding with the current model is simply shortage of time. This kind of simulation model necessarily involves learning by doing, so we started with the shocks that we had used in our prior work. But Western economies were, in fact, facing adverse supply shocks in 2007–08, in the guise of rising energy and commodity prices, and these played a role in worsening the current downturn. Furthermore, our simulations include examples of changes in financial conditions, such as changes in the money stock (interest rates) and in bank capital endowments, so we can potentially explore how financial policy measures (including government recapitalization of banks) may affect the outcome. Nevertheless, this should be treated as a preliminary exercise.

The plan of the paper is as follows. In section 1, we briefly reprise the basic structure of the Goodhart-Sunirand-Tsomocos (GST) model and detail the innovations that we have made here. Section 2 sets out how the model works and its clearing conditions. In section 3, we report our choice of exogenous parameters for our numerical simulation and describe the resulting equilibrium values. In section 4, we report on the comparative statics of changes in the parameters chosen, and section 5 concludes.

With such a large, and alas complicated, model, there are a vast number of exercises that could be run, each with an accompanying set of tables and diagrams. In one sense this is a strength of the approach, since it supports the examination of a huge variety of potential shocks and policy responses, both individually and in conjunction. At the same time, however, it can lead to a mind-boggling multiplication of detail. In pursuit of focus and comparative simplicity, we focus here on just four examples: a decrease in the money supply in the initial period; an increased desire to take on risk (as occurred in 2003–06), which leads to adverse shocks having a stronger effect on the system; a (foreseen) intervention by the authorities to provide liquidity assistance in very bad states; and a combination of the former two simultaneously, which allows us to examine the extent to which the resulting effects are nonlinear.

1. The Background Setup

Goodhart, Sunirand, and Tsomocos (2004, 2006) and Tsomocos (2003) develop models of financial stability that are rich enough to include defaultable consumer loan, deposit, and interbank markets. In the models, consumers maximize their expected utility from consumption of goods, and banks maximize their expected profits. The main financial imperfection in Goodhart, Sunirand, and Tsomocos (2004, 2006) is that they assume that individual bank borrowers are assigned, by history or by informational constraints, to borrow from a single bank. Money is introduced by a cash-in-advance constraint, whereby a private agent needs money to buy commodities from other agents; commodities cannot be used to buy commodities. Similarly, they assume that agents needing money can always borrow cheaper from their (assigned) bank than from other agents; banks have an informational (and perhaps scale) advantage that gives them a role as an intermediary. The amount of loans they repay is a choice variable for consumers, so default in these models is endogenous.

The general model (Goodhart, Sunirand, and Tsomocos, 2006) features a set of heterogeneous private sector agents with initial endowments of both money and commodities; it is an endowment model without production. There is also a set of heterogeneous banks, who similarly have differing initial allocations of capital (in the form of government bonds). There are two other players, a central bank that can inject extra money into the system through open market operations (OMOs), and a financial supervisory agency, which can set minimum liquidity and capital requirements and imposes penalties on failures to meet such requirements and on defaults.

The main purpose of this paper is to model the market for mortgages and examine the implications of default in bank lending and of a housing market crisis. To do so, we alter the above framework in the following ways.

—First, we introduce another good into the economy, which is durable and gives utility in every period. The utility of consuming this good resembles the utility from buying a house. For tractability, the durable good (house) is assumed to be infinitely divisible.

—Second, we explicitly model a market for mortgages. Consumers enter a mortgage contract to buy housing, which they pledge as collateral. They default on their mortgage when the endogenous value of collateral is less than the amount they have to repay (Geanakoplos,

2003; Geanakoplos and Zame, 1997). When they default, the bank seizes the amount of housing pledged as collateral and immediately offers it in the next period housing market. In this sense default is highly discontinuous, as consumers do not choose the exact amount they want to default (as in the model discussed above), but only decide on whether to default.[1]

—Third, we introduce a new agent, λ, who is only born in period two. The motivation behind this is that the healthy functioning of the housing market generally depends on the existence of first-time buyers.

—Fourth, we allow for short-term loan markets operating within each period. This was not necessary in the Goodhart, Sunirand, and Tsomocos models, but in our analysis it plays a crucial role in providing credit to first-time buyers, namely, Mr. λ. For consistency, all agents can borrow short-term. In this market, there is no uncertainty regarding repayment. The central bank intervenes in the short-term loan markets in the second period to keep the interest rates (in the good state) at reasonable levels.

—Finally, since we are not considering wider asset markets, we exclude capital requirements for banks from our analysis.

2. The Model

Given the limited participation in the loan markets in our model, we need at least four agent-households (α, β, ϕ, λ) and two commercial banks (γ, δ). There are two periods and S states of the world. All agents maximize their utility over the consumption of the good and of housing in every period $t \in T = (0, 1)$ and state $s \in S$. Banks maximize their expected profits in the second period. The set of all states is given by $s \in S^* = \{0\} \cup S$.

Agent $h \in (\alpha, \beta)$ is endowed with the good at every $s \in S^*$, whereas agent λ is endowed at every $s \in S$, since he enters the economy only in the second period. Agent ϕ is endowed with houses only at $t = 0$. Agents α and ϕ interact with bank γ, while agents β and λ are associated with bank δ. All households are also given government cash free and clear of any obligations ($m_{s^*} \geq 0$). Both endowments and cash are allowed to vary across states of nature.

The central bank acts in the interbank market at $t = 0$ by providing liquidity M^{CB} and in the short-term loan markets at $t = 1$

1. Shubik and Wilson (1977) and Dubey, Geanakoplos, and Shubik (2005) analyze continuous default.

by providing liquidity $M^{CB}_{\gamma s}$ and $M^{CB}_{\delta s}$ in the markets organized by banks γ and δ, respectively.

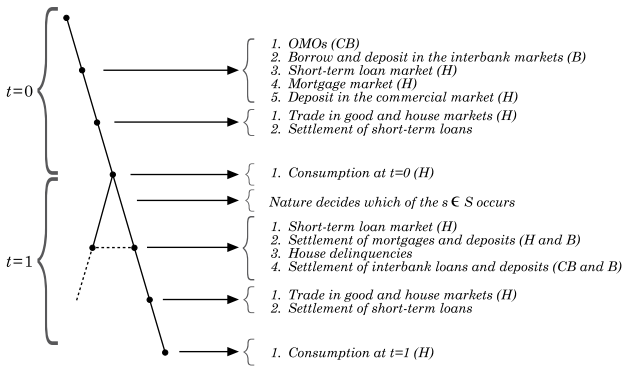
In the following subsections, we give the timeline of our model and specify the optimization problems for all the participants in the economy.

2.1 The Time Structure of Markets

In each period $t \in T$, six markets meet: the short-term (intraperiod) loan, mortgage, deposit, and interbank (intertemporal) markets meet simultaneously, and then the good and housing markets meet. Short-term loans come due at the end of the period. This setup maximizes the number of transactions possible and allows agents to borrow in the short-term money market in order to invest in the long-term bond or asset market. It also allows for an explicit speculative motive for holding money. Agents have the option of investing cash in the short loan market and then carrying it over to the next period. The only reason they may not do this is that they believe they will get a higher return from holding deposits. This not only preserves Keynesian motives on the uses of money, but also provides a rationale for an upward-sloping term structure.

Figure 1 indicates our time line, including the moments at which the various loans and assets come due. We make the sequence precise when we formally describe the budget set.

Figure 1. Time Line[a]



Source: Authors' drawing.
a. CB: central bank; B: commercial banks; H: households.

2.2 Household α's and β's Optimization Problem

Each consumer $h \in \{\alpha, \beta\}$ maximizes his payoff, which is his utility from consumption of the good and the house.[2] In order to acquire housing he enters a mortgage contract, which he has to repay in the last period. The amount of housing that he purchases is pledged as collateral. He honors his mortgage when the value of the housing that he has bought is greater than the amount he has to repay. If it is lower, then he defaults on his mortgage and the bank that extended the mortgage seizes the collateral. In essence, he repays the minimum between the two values, that is, min(value of collateral, mortgage amount). We denote by $S_1^h \subset S$ the set of states that agent h does not default on his mortgage, that is, S_1^h: value of collateral $\geq$ mortgage amount}. The maximization problem is as follows:

$$\max_{q_{s1}^h, b_{s2}^h, \mu_s^h, \bar{\mu}^h} \Pi^h = u(e_{01}^h - q_{01}^h) + u\left(\frac{b_{02}^h}{p_{02}}\right) + \sum_{s \in S} \theta_s u(e_{s1}^h - q_{s1}^h)$$
$$+ \sum_{s \in S^1} \theta_s u\left(\frac{b_{02}^h}{p_{02}} + \frac{b_{s2}^h}{p_{s2}}\right) + \sum_{s \notin S^1} \theta_s u\left(\frac{b_{s2}^h}{p_{s2}}\right)$$

subject to

$$b_{02}^h \leq \frac{\mu_0^h}{1 + r_0^k} + \frac{\bar{\mu}^h}{1 + \bar{r}^k} + m_0^h \tag{1}$$

(that is, the expenditure for housing at $t = 0 \leq$ amount borrowed short-term at $t = 0$ + mortgage amount + initial private monetary endowment);

$$\mu_0^h \leq p_{01} q_{01}^h \tag{2}$$

(that is, short-term loan repayment $\leq$ good sales at $t = 0$);

$$b_{s2}^h + \bar{\mu}^h \leq \frac{\mu_s^h}{1 + r_s^k} + m_s^h, \ \forall\, s \in S_1^h \tag{3}$$

(that is, expenditure for housing in the second period, state $s \in S_1^h$ + mortgage repayment $\leq$ amount borrowed short-term + private monetary endowment in $s \in S_1^h$);

2. In our simulations, we use a constant relative risk aversion (CRRA) utility function to account for wealth effects.

$$\mu_s^h \leq p_{s1} q_{s1}^h, \ \forall \ s \in S_1^h \tag{4}$$

(that is, short-term loan repayment $\leq$ good sales in $s \in S_1^h$);

$$b_{s2}^h \leq \frac{\mu_s^h}{1 + r_s^k} + m_s^h, \ \forall \ s \notin S_1^h \tag{5}$$

(that is, expenditure for housing in the second period, state $s \notin S_1^h \leq$ amount borrowed short term + private monetary endowment in $s \notin S_1^h$);

$$\mu_s^h \leq p_{s1} q_{s1}^h, \ \forall \ s \notin S_1^h \tag{6}$$

(that is, short-term loan repayment $\leq$ good sales in $s \notin S_1^h$); and

$$q_{s1}^h \leq e_{s1}^h, \ \forall \ s \in S^* \tag{7}$$

(that is, quantity of goods sold in $s \leq$ endowment of goods in s);

where

$k = \gamma$ for $h = \alpha$ and $k = \delta$ for $h = \beta$;
$b_{s2}^h \equiv$ amount of fiat money spent by $h \in H$ to trade in the housing market in $s \in S^*$;
$q_{s2}^h \equiv$ amount of goods offered for sale by $h \in H$ in $s \in S^*$;
$\bar{\mu}^h \equiv$ mortgage amount that $h \in H$ takes out;
$\mu_s^h \equiv$ short-term borrowing by $h \in H$ in $s \in S^*$;
$\bar{r}^k \equiv$ mortgage rate offered by bank k;
$r_s^k \equiv$ short-term rate offered by bank k in $s \in S^*$;
$p_{s1} \equiv$ price of the good in $s \in S^*$;
$p_{s2} \equiv$ price of housing in $s \in S^*$;
$e_{s1}^h \equiv$ endowment of goods of $h \in H$ in $s \in S^*$; and
$m_s^h \equiv$ monetary endowment of $h \in H$ in $s \in S^*$.

2.3 Household ϕ's Optimization Problem

Agent ϕ is endowed with housing at $t = 0$, some (much) of which he sells to buy goods for consumption. He then deposits interperiod a part of the sales receipts for use in the second period. His maximization problem is as follows:

$$\max_{q_{s2}^{\phi}, b_{s1}^{\phi}, \bar{d}^{\phi}, \mu_s^{\phi}} \Pi^{\phi} = u\left(\frac{b_{01}^{\phi}}{p_{01}}\right) + u\left(e_{02}^{\phi} - q_{02}^{\phi}\right) + \sum_{s \in S} \theta_s u\left(\frac{b_{s1}^{\phi}}{p_{s1}}\right) + \sum_{s} \theta_s u\left(e_{02}^{\phi} - q_{02}^{\phi} - q_{s2}^{\phi}\right)$$

subject to

$$b_{01}^{\phi} + \bar{d}^{\phi} \leq \frac{\mu_0^{\phi}}{1 + r_0^{\gamma}} + m_0^{\phi} \tag{8}$$

(that is, expenditure for goods + interperiod deposits $\leq$ amount borrowed short-term + private monetary endowment at $t = 0$);

$$\mu_0^{\phi} \leq p_{02} q_{02}^{\phi} \tag{9}$$

(that is, short-term loan repayment $\leq$ housing sales at $t = 0$);

$$q_{02}^{\phi} \leq e_{02}^{\phi} \tag{10}$$

(that is, quantity of housing sold at $t = 0 \leq$ endowment of housing at $t = 0$);

$$b_{s1}^{\phi} \leq \frac{\mu_s^{\phi}}{1 + r_s^{\gamma}} + \bar{d}^{\phi}(1 + \bar{r}_d) + m_s^{\phi} \quad \forall\, s \in S \tag{11}$$

(that is, expenditure of goods $\leq$ amount borrowed short term + deposits and interest payment + private monetary endowment in s);

$$\mu_s^{\phi} \leq p_{s2} q_{s2}^{\phi} \quad \forall\, s \in S \tag{12}$$

(that is, short-term loan repayment $\leq$ housing sales in s); and

$$q_{s2}^{\phi} \leq e_{02}^{\phi} - q_{02}^{\phi} \quad \forall\, s \in S \tag{13}$$

(that is, quantity of housing sold in $s \leq$ endowment of housing at $t = 0$ – quantity of housing sold $t = 0$);

where

$b_{s1}^{\phi} \equiv$ amount of fiat money spent by ϕ to trade in the goods market in $s \in S^*$;

$q_{s2}^{\phi} \equiv$ amount of housing offered for sale by ϕ in $s \in S^*$;
$\bar{d}^{\phi} \equiv$ deposit amount for ϕ;
$\mu_s^{\phi} \equiv$ short-term borrowing by ϕ in $s \in S^*$;
$\bar{r}_d \equiv$ deposit rate;
$r_s^{\gamma} \equiv$ short-term rate offered by bank γ in $s \in S^*$;
$e_{02}^{\phi} \equiv$ endowment of housing of ϕ at $t = 0$; and
$m_s^{\phi} \equiv$ monetary endowment of ϕ in $s \in S^*$.

2.4 Household λ's Optimization Problem

Agent λ enters the economy in the second period and is endowed with goods. His maximization problem is as follows:

$$\max_{q_{s1}^{\lambda}, b_{s2}^{\lambda}, \mu_s^{\lambda}} \Pi^{\lambda} = \sum_{s \in S} \theta_s u\,(e_{s1}^{\lambda} - q_{s1}^{\lambda}) + \sum_{s \in S} \theta_s u\left(\frac{b_{s2}^{\lambda}}{p_{s2}}\right)$$

subject to

$$b_{s2}^{\lambda} \leq \frac{\mu_s^{\lambda}}{1 + r_s^{\delta}} + m_s^{\lambda} \quad \forall\, s \in S \tag{14}$$

(that is, expenditure for housing $\leq$ amount borrowed short-term + private monetary endowment in s);

$$\mu_s^{\lambda} \leq p_{s1} q_{s1}^{\lambda} \quad \forall\, s \in S \tag{15}$$

(that is, short-term loan repayment $\leq$ good sales in s); and

$$q_{s1}^{h} \leq e_{s1}^{h} \quad \forall\, s \in S \tag{16}$$

(that is, quantity of goods sold in $s \leq$ endowment of goods in s);

where

$b_{s2}^{\lambda} \equiv$ amount of fiat money spent by λ to trade in the housing market in $s \in S$;
$q_{s1}^{\lambda} \equiv$ amount of goods offered for sale by λ in $s \in S$;
$\mu_s^{\lambda} \equiv$ short-term borrowing by λ in $s \in S$;
$r_s^{\delta} \equiv$ short-term rate offered by bank δ in $s \in S$;
$e_{s1}^{\lambda} \equiv$ endowment of goods of λ in $s \in S$; and
$m_s^{\lambda} \equiv$ monetary endowment of λ in $s \in S$;

2.5 Bank γ's Optimization Problem

Bank γ (as also bank δ) maximizes its expected profits in the second period. In the first period, it borrows from the interbank market, since it is relatively poor in initial capital, and extends credit in the short-term loan and mortgage markets. It also receives deposits from ϕ. In the second period, it receives the repayment on the mortgage it extended (full repayment for $s \in S_1^{\alpha}$ and partial repayment otherwise, since the value of the collateral is less than the amount of the mortgage), repays its interbank and deposit borrowing, and extends short-term credit. Its maximization problem is as follows:[3]

$$\max_{\pi_s^{\gamma}, m_s^{\gamma}, \bar{m}^{\gamma}, \mu_I^{\gamma}, \bar{\mu}_d^{\gamma}} \Pi^{\gamma} = \sum_{s \in S} \theta_s \left[\pi_s^{\gamma} - c^{\gamma} \left(\pi_s^{\gamma} \right)^2 \right]$$

subject to

$$m_0^{\gamma} + \bar{m}^{\gamma} \leq \frac{\mu_I^{\gamma}}{1+\rho} + \frac{\bar{\mu}_d^{\gamma}}{1+\bar{r}_{\mathrm{d}}} + e_0^{\gamma} \tag{17}$$

(that is, short-term lending + mortgage extension ≤ interbank loans + consumer deposits + initial capital endowment at $t = 0$);

$$m_s^{\gamma} + \bar{\mu}_d^{\gamma} + \mu_I^{\gamma} \leq \bar{m}^{\gamma}(1+\bar{r}_s^{\gamma}) + m_0^{\gamma}(1+r_0^{\gamma}) + e_s^{\gamma} \quad \forall\, s \in S \tag{18}$$

(that is, short-term lending + deposit repayment + interbank loan repayment ≤ effective mortgage repayment + first period short-term loan repayment + capital endowment in $s \in S$); and

$$\pi_s^{\gamma} = m_s^{\gamma}(1+r_s^{\gamma}) \;\forall\, s \in S \tag{19}$$

(that is, profits = short-term loans repayment $s \in S$);

where
$\pi_s^{\gamma} \equiv$ bank γ's profits at state $s \in S$;

3. Banks' risk aversion is captured via a quadratic objective function, as in essence they are facing a portfolio problem and we want to capture diversification effects as closely as possible.

$\bar{m}^{\gamma} \equiv$ mortgage extension by bank γ;
$m_s^{\gamma} \equiv$ short-term loan extension by bank γ at state $s \in S^*$;
$\mu_I^{\gamma} \equiv$ interbank borrowing by bank γ;
$\bar{\mu}_d^{\gamma} \equiv$ amount borrowed from consumers in the form of deposits by bank γ;
$\bar{r}_s^{\gamma} \equiv$ effective repayment rate on the mortgage at state $s \in S$;
$r_s^{\gamma} \equiv$ short-term rate offered by bank γ in $s \in S^*$;
$\rho \equiv$ interbank rate; and
$e_s^{\gamma} \equiv$ capital endowment of bank γ at state $s \in S^*$.

2.6 Bank δ's Optimization Problem

Bank δ maximizes its expected profits in the second period. In the first period, it deposits in the interbank market, since it is relatively rich in initial capital, and extends credit in the short-term loan and mortgage markets. In the second period, it receives the repayment on the mortgage it extended (full repayment for $s \in S_1^{\beta}$ and partial repayment otherwise, since the value of the collateral is less than the amount of the mortgage), receives payment from depositing in the interbank market, and extends short-term credit. Its maximization problem is as follows:

$$\max_{\pi_s^{\delta}, m_s^{\delta}, \bar{m}^{\delta}, d_I^{\delta}} \Pi^{\delta} = \sum_{s \in S} \theta_s \left[\pi_s^{\delta} - c^{\delta} \left(\pi_s^{\delta} \right)^2 \right]$$

subject to

$$m_0^{\delta} + \bar{m}^{\delta} + d_I^{\delta} \leq e_0^{\delta} \tag{20}$$

(that is, short-term lending + mortgage extension + interbank deposits ≤ initial capital endowment at $t = 0$);

$$m_s^{\delta} \leq \bar{m}^{\delta}(1 + \bar{r}_s^{\delta}) + m_0^{\delta}(1 + r_0^{\delta}) + d_I^{\delta}(1 + \rho) + e_s^{\delta} \quad \forall\, s \in S \tag{21}$$

(that is, short-term lending ≤ effective mortgage repayment + first period short-term loan repayment + interbank deposits and interest payment + capital endowment in $s \in S$); and

$$\pi_s^{\delta} = m_s^{\delta}(1 + r_s^{\delta}) \quad \forall\, s \in S \tag{22}$$

(that is, profits = short-term loans repayment $s \in S$);

where

$\pi_s^\delta \equiv$ bank δ's profits at state $s \in S$;
$\bar{m}^\delta \equiv$ mortgage extension by bank δ;
$m_s^\delta \equiv$ short-term loan extension by bank δ at state $s \in S^*$;
$d_I^\delta \equiv$ interbank deposits by bank δ;
$\bar{r}_s^\delta \equiv$ effective repayment rate on the mortgage at state $s \in S$;
$r_s^\delta \equiv$ short-term rate offered by bank δ in $s \in S^*$; and
$e_s^\delta \equiv$ capital endowment of bank δ at state $s \in S^*$.

2.7 Market Clearing Conditions

There are six market categories in our model (namely, goods, housing, mortgage, short-term loan, consumer deposit, and interbank markets). Each of these markets determines a price that equilibrates demand and supply in equilibrium.

2.7.1 The goods market

The goods market clears when the amount of money offered for goods is exchanged for the quantity of goods offered for sale:

$$p_{01} = \frac{b_{01}^\phi}{q_{01}^\alpha + q_{01}^\beta}; \tag{23}$$

$$p_{s1} = \frac{b_{s1}^\phi}{q_{s1}^\alpha + q_{s1}^\beta + q_{s1}^\lambda} \quad \forall\, s \in S. \tag{24}$$

2.7.2 The housing market

The housing market clears when the amount of money offered for housing is exchanged for the quantity of housing offered for sale:

$$p_{02} = \frac{b_{02}^\alpha + b_{02}^\beta}{q_{02}^\phi}; \tag{25}$$

$$p_{s2} = \frac{b_{s2}^\alpha + b_{s2}^\beta + b_{s2}^\lambda}{q_{s2}^\phi} \quad \text{for } s \in S_1^\alpha \cap S_1^\beta; \tag{26}$$

$$p_{s2} = \frac{b_{s2}^{\alpha} + b_{s2}^{\beta} + b_{s2}^{\lambda}}{q_{s2}^{\phi} + (b_{02}^{\alpha} / p_{02})} \quad \text{for } s \in S_1^{\beta} \setminus S_1^{\alpha} \cap S_1^{\beta}; \tag{27}$$

$$p_{s2} = \frac{b_{s2}^{\alpha} + b_{s2}^{\beta} + b_{s2}^{\lambda}}{q_{s2}^{\phi} + (b_{02}^{\beta} / p_{02})} \quad \text{for } s \in S_1^{\alpha} \setminus S_1^{\alpha} \cap S_1^{\beta}; \tag{28}$$

$$p_{s2} = \frac{b_{s2}^{\alpha} + b_{s2}^{\beta} + b_{s2}^{\lambda}}{q_{s2}^{\phi} + (b_{02}^{\alpha} / p_{02}) + (b_{02}^{\beta} / p_{02})} \quad \text{for } s \notin S_1^{\alpha} \cup S_1^{\beta}. \tag{29}$$

When agent $h \in \{\alpha, \beta\}$ defaults on his mortgage, the amount of housing he has pledged as collateral will be offered by his bank for sale in the market. This amount is equal to the amount of housing he purchased in the initial period, that is, b_{02}^{h} / p_{02}. For example, in state $s \in S_1^{\beta} \setminus S_1^{\alpha} \cap S_1^{\beta}$, agent α (but not β) defaults, so the amount of housing he purchased in the initial period and pledged as collateral will be offered for sale by bank γ.

2.7.3 The mortgage market

Given that

$$1 + \bar{r}^{k} = \frac{\bar{\mu}^{h}}{\bar{m}^{k}}, \tag{30}$$

the effective return on the mortgage is min(value of collateral, mortgage amount) / initial credit extension, or

$$1 + \bar{r}_{s}^{k} = \frac{\min\left[(b_{02}^{h} / p_{02}) p_{s2}, \bar{\mu}^{h}\right]}{\bar{m}^{k}},$$

where $k = \gamma$ for $h = \alpha$ and $k = \delta$ for $h = \beta$. We thus get the following clearing conditions for effective returns on mortgages:

$$1 + \bar{r}_{s}^{k} = 1 + \bar{r}^{k} \quad \text{for } s \in S_1^{h} = \left\{ s \in S : \bar{\mu}^{h} \leq \frac{b_{02}^{h}}{p_{02}} p_{s2} \right\}; \tag{31}$$

$$1 + \bar{r}_{s}^{k} = (1 + \bar{r}^{k}) \frac{b_{02}^{h}}{\bar{\mu}^{h}} \frac{p_{s2}}{p_{02}} \quad \text{for } s \notin S_1^{h}. \tag{32}$$

2.7.4 The short-term loan market

$$1+r_0^{\gamma}=\frac{\mu_0^{\alpha}+\mu_0^{\phi}}{m_0^{\gamma}}; \tag{33}$$

$$1+r_s^{\gamma}=\frac{\mu_s^{\alpha}+\mu_s^{\phi}}{m_s^{\gamma}+M_{\gamma s}^{CB}}; \tag{34}$$

$$1+r_0^{\delta}=\frac{\mu_0^{\beta}}{m_0^{\delta}}; \tag{35}$$

$$1+r_s^{\delta}=\frac{\mu_s^{\beta}+\mu_s^{\lambda}}{m_s^{\delta}+M_{\delta s}^{CB}}. \tag{36}$$

2.7.5 The consumer deposit market

$$1+\bar{r}_d=\frac{\bar{\mu}_d^{\gamma}}{\bar{d}^{\phi}}. \tag{37}$$

2.7.6 The interbank market

$$1+\rho=\frac{\mu_I^{\gamma}}{d_I^{\delta}+M^{CB}}. \tag{38}$$

2.8 Definition of Equilibrium

Let $\sigma^h=(q_{s1}^h,b_{s2}^h,\mu_s^h,\bar{\mu}^h)\in\mathbb{R}^{s+1}\times\mathbb{R}^{s+1}\times\mathbb{R}^{s+1}\times\mathbb{R}$ for $h\in\{\alpha,\beta\}$;

$$\sigma^{\phi}=(q_{s2}^{\phi},b_{s1}^{\phi},\bar{d}^{\phi},\mu_s^{\phi})\in\mathbb{R}^{s+1}\times\mathbb{R}^{s+1}\times\mathbb{R}\times\mathbb{R}^{s+1};$$

$$\sigma^{\lambda}=(q_{s1}^{\lambda},b_{s2}^{\lambda},\mu_s^{\lambda})\in\mathbb{R}^{s}\times\mathbb{R}^{s}\times\mathbb{R}^{s};$$

$$\sigma^{\gamma}=(\pi_s^{\gamma},m_s^{\gamma},\bar{m}^{\gamma},\mu_I^{\gamma},\bar{\mu}_d^{\gamma})\in\mathbb{R}^{s}\times\mathbb{R}^{s+1}\times\mathbb{R}\times\mathbb{R};$$

$$\sigma^{\delta}=(\pi_s^{\delta},m_s^{\delta},\bar{m}^{\delta},d_I^{\delta})\in\mathbb{R}^{s}\times\mathbb{R}^{s+1}\times\mathbb{R}\times\mathbb{R}.$$

Also, let $\eta = (p_{s1}, p_{s2}, r_s^{\gamma}, r_s^{\delta}, \bar{r}^{\gamma}, \bar{r}_s^{\gamma}, \bar{r}^{\delta}, \bar{r}_s^{\delta}, \rho)$

$$\in \mathbb{R}^{s+1} \times \mathbb{R}^{s+1} \times \mathbb{R}^{s+1} \times \mathbb{R}^{s+1} \times \mathbb{R} \times \mathbb{R}^{s} \times \mathbb{R} \times \mathbb{R}^{s} \times \mathbb{R};$$

$$B^h(\eta) = \left\{\sigma^h : \text{eqs. } (1)-(7) \text{ hold}\right\} \quad \text{for } h \in \left\{\alpha, \beta\right\};$$

$$\mathrm{B}^{\phi}(\eta) = \left\{\sigma^{\phi} : \text{eqs. } (8)-(13) \text{ hold}\right\};$$

$$B^{\lambda}(\eta) = \left\{\sigma^{\lambda} : \text{eqs.}(14)-(16) \text{ hold}\right\};$$

$$B^{\gamma}(\eta) = \left\{\sigma^{\gamma} : \text{eqs.}(17)-(19) \text{ hold}\right\}; \quad \text{and}$$

$$B^{\delta}(\eta) = \left\{\sigma^{\delta} : \text{eqs.}(20)-(22) \text{ hold}\right\}.$$

We say that $(\sigma^{\alpha}, \sigma^{\beta}, \sigma^{\phi}, \sigma^{\lambda}; p_{s1}, p_{s2}, r_s^{\gamma}, r_s^{\delta}, \bar{r}^{\gamma}, \bar{r}_s^{\gamma}, \bar{r}^{\delta}, \bar{r}_s^{\delta}, \rho)$ is a monetary equilibrium with commercial banks, collateral, and default if

(a) $\sigma^{\mathrm{n}} \in \mathrm{Argmax}_{\sigma^{\mathrm{n}} \in \mathrm{B}^{\mathrm{n}}(\eta)} \Pi^{\mathrm{n}}$, $n \in \{\alpha, \beta, \phi, \lambda\}$

and

(b) $\sigma^{\mathrm{k}} \in \mathrm{Argmax}_{\sigma^{\mathrm{k}} \in \mathrm{B}^{\mathrm{k}}(\eta)} \Pi^{\mathrm{k}}$, $k \in \{\gamma, \delta\}$

and if all markets in equations (23) through (38) clear.

3. Discussion of Equilibrium

In this section, we investigate a parametrized version of the model whereby only three states of nature are possible in the second period. We have chosen the exogenous parameters in our model so as to illustrate a housing and mortgage crisis. Their initial values are

presented in table 1. The initial equilibrium yielded by the model is presented in table 2 and analyzed below.

Table 1. Exogenous Variables

Coefficient of risk aversion	*Endowment*	*Housing*	*Money*	*Capital*	*Other*
$c^{\alpha} = 1.3$	$e_{01}^{\alpha} = 11$	$e_{02}^{\phi} = 5.5$	$m_0^{\alpha} = 0.1$	$e_0^{\gamma} = 4$	$M^{CB} = 65$
$c^{\beta} = 1.3$	$e_{11}^{\alpha} = 10$		$m_1^{\alpha} = 0.1$	$e_1^{\gamma} = 0.7$	$M_{\gamma 1}^{CB} = 10.9$
$c^{\phi} = 1.3$	$e_{21}^{\alpha} = 10$		$m_2^{\alpha} = 4.4$	$e_2^{\gamma} = 0.7$	$M_{\gamma 2}^{CB} = 8$
$c^{\gamma} = 1.3$	$e_{31}^{\alpha} = 0.7$		$m_3^{\alpha} = 0.1$	$e_3^{\gamma} = 0.7$	$M_{\gamma 3}^{CB} = 0.5$
$c^{\gamma} = 0.005$	$e_{01}^{\beta} = 2$		$m_0^{\beta} = 5.8$	$e_0^{\delta} = 13$	$M_{\delta 1}^{CB} = 2.4$
$c^{\delta} = 0.005$	$e_{11}^{\beta} = 7$		$m_1^{\beta} = 0.1$	$e_1^{\delta} = 1$	$M_{\delta 2}^{CB} = 0.8$
	$e_{21}^{\beta} = 3$		$m_2^{\beta} = 0.1$	$e_2^{\delta} = 1$	$M_{\delta 3}^{CB} = 0.5$
	$e_{31}^{\beta} = 0.1$		$m_3^{\beta} = 0.1$	$e_3^{\delta} = 1$	$\theta_1 = 0.90$
	$e_{11}^{\lambda} = 4$		$m_0^{\phi} = 0.1$		$\theta_2 = 0.075$
	$e_{21}^{\lambda} = 4$		$m_1^{\phi} = 0.1$		$\theta_3 = 0.025$
	$e_{31}^{\lambda} = 3$		$m_2^{\phi} = 0.1$		
			$m_3^{\phi} = 0.1$		
			$m_1^{\lambda} = 0.1$		
			$m_2^{\lambda} = 0.1$		
			$m_3^{\lambda} = 0.1$		

e_{s1}: Endowment of goods in state $s \in S^*$.
e_{02}: Endowment of houses at $t = 0$.
m_s: Private money held by households in state $s \in S^*$.
e_0: Initial capital of banks.
e_s: Additional capital of banks in state $s \in S$.
M^{CB}: Money supply at $t = 0$.
M_{ks}^{CB}: Money injection by the central bank in the short-term loan market organized by bank $k \in \{\gamma, \delta\}$ in state $s \in S$.
θ_s: Probability of state $s \in S$.

In the initial equilibrium, we examine three different scenarios that can occur in the second period. State 1 occurs with the highest probability, and state 2 is more probable than state 3. State 1 is the good period in which neither borrower defaults. In state 2, one of the two agents, Mr. β, defaults on his mortgage debt, but the other does not. In state 3, both default. Agent α is richer in endowments of the good in the first period, whereas agent β is relatively richer in state 2 in the second period. Bank γ has less initial capital than bank δ, while it has more capital in the second period. The capital of both banks in the second period can be interpreted as outside banking profits or capital injections obtained in the second period and will play a crucial role in the comparative statics we perform. We have chosen the parametrization to motivate lending in the interbank market and in particular to motivate bank δ to deposit in the interbank rate.

The level of default on the mortgages depends on the relative (second period) differential between the value of houses that each agent bought and the mortgage amount they have to repay. Agent α, who is richer in the first period, needs to take a comparatively lower loan-to-value mortgage for the amount of housing he wants to purchase than agent β, since he can finance the purchase through the sale of goods in the first period. As a result, the effective return to the lending bank on the mortgages in state 3, when both agents default, will be higher for α than β. In combination with the fact that α does not default in state 2, this results in a lower interest rate on the mortgage for α than for β, since rational expectations are assumed throughout.

In our simulation, the prices of the good and the house move in opposite directions in the second period. The good is relatively more expensive in state 2 than state 1 and in state 3 than state 2, whereas the opposite holds for the price of the house. The intuition behind the result is quite simple, since the model is driven by adverse supply shocks to goods endowments, worse in state 3 than in state 2. Agents default on their mortgages when the value of the house is low. This happens when the endowments of goods are low (that is, an adverse supply shock) since agents will not have enough income to allocate to the housing market. This, in turn, implies that the price of the good should rise.

In order to buy the house, agents α and β sell goods in the first period and also take out a mortgage. This creates income for ϕ, the initial owner of the housing stock, who uses a portion to purchase

Table 2. Initial Equilibrium

Prices	*Interest rates*	*Loans/deposits households*	*Loans/deposits households*	*Loans/deposits banks*	*Repayment rates on mortgages*	*Goods*	*Houses*
$p_{01} = 4.10$	$\bar{r}^{\gamma} = 0.079$	$\bar{\mu}^{\alpha} = 12.33$	$\mu_1^{\lambda} = 6.23$	$\bar{m}^{\gamma} = 11.43$	$v_1^{\alpha} = 100\%$	$q_{01}^{\alpha} = 7.20$	$b_{02}^{\alpha} = 49.78$
$p_{11} = 2.60$	$\bar{r}^{\delta} = 0.123$	$\mu_0^{\alpha} = 29.47$	$\mu_2^{\lambda} = 6.97$	$\bar{\mu}_d^{\gamma} = 25.50$	$v_2^{\alpha} = 100\%$	$q_{11}^{\alpha} = 4.42$	$q_{12}^{\alpha} = 0.09$
$p_{21} = 3.10$	$r_0^{\gamma} = 0.043$	$\mu_1^{\alpha} = 12.80$	$\mu_3^{\lambda} = 18.46$	$\bar{\mu}_I^{\gamma} = 69.07$	$v_3^{\alpha} = 62\%$	$q_{21}^{\alpha} = 4.48$	$b_{22}^{\alpha} = 5.12$
$p_{31} = 12.31$	$r_1^{\gamma} = 0.047$	$\mu_2^{\alpha} = 13.65$		$m_0^{\gamma} = 83.24$	$v_1^{\beta} = 100\%$	$q_{31}^{\alpha} = 0.35$	$b_{32}^{\alpha} = 1.24$
$p_{02} = 26.12$	$r_2^{\gamma} = 0.047$	$\mu_3^{\alpha} = 4.35$		$m_1^{\gamma} = 5.28$	$v_2^{\beta} = 62\%$	$q_{01}^{\beta} = 0.29$	$b_{02}^{\beta} = 17.58$
$p_{12} = 15.17$	$r_3^{\gamma} = 2.83$	$\bar{\mu}^{\beta} = 11.96$		$m_2^{\gamma} = 5.28$	$v_3^{\beta} = 28\%$	$q_{11}^{\beta} = 4.54$	$q_{12}^{\beta} = 0.04$
$p_{22} = 10.96$	$r_0^{\delta} = 0.043$	$\mu_0^{\beta} = 1.18$		$m_3^{\gamma} = 0.64$		$q_{21}^{\beta} = 1.71$	$b_{22}^{\beta} = 5.08$
$p_{32} = 5.04$	$r_1^{\delta} = 0.048$	$\mu_1^{\beta} = 12.43$		$\bar{m}^{\delta} = 10.65$		$q_{31}^{\beta} = 0.04$	$b_{32}^{\beta} = 0.29$
	$r_2^{\delta} = 0.049$	$\mu_2^{\beta} = 5.22$		$d_I^{\delta} = 1.22$		$b_{01}^{\phi} = 30.64$	$q_{02}^{\phi} = 2.20$
	$r_3^{\delta} = 1.58$	$\mu_3^{\beta} = 0.50$		$m_0^{\delta} = 1.13$		$b_{11}^{\phi} = 29.55$	$q_{12}^{\phi} = 0.27$
	$\bar{r}_d = 0.043$	$\bar{d}^{\phi} = 24.44$		$m_1^{\delta} = 15.41$		$b_{21}^{\phi} = 25.84$	$q_{22}^{\phi} = 0.03$
	$\rho = 0.043$	$\mu_0^{\phi} = 57.36$		$m_2^{\delta} = 10.82$		$b_{31}^{\phi} = 23.30$	$b_{32}^{\phi} = 2.30$

Table 2. (continued)

Prices	*Interest rates*	*Loans/deposits households*	*Loans/deposits households*	*Loans/deposits banks*	*Repayment rates on mortgages*	*Goods*	*Houses*
		$\mu_1^{\phi} = 4.14$		$m_3^{\delta} = 6.84$		$q_{11}^{\lambda} = 2.40$	$b_{12}^{\lambda} = 6.05$
		$\mu_2^{\phi} = 0.25$				$q_{21}^{\lambda} = 2.29$	$b_{22}^{\lambda} = 6.75$
						$q_{31}^{\lambda} = 1.50$	$b_{32}^{\lambda} = 7.25$

Source: Authors' calculations.

p_{s1}: Price of goods in state $s \in S^*$.
p_{s2}: Price of houses in state $s \in S^*$.
$\bar{r}_d$: Consumer deposit rate.
ρ: Interbank rate.
$\bar{\mu}$: Mortgage amount.
μ_s: Short-term borrowing by households in state $s \in S^*$.
$\bar{d}^{\phi}$: Deposit by agent ϕ at t = 0.
$\bar{m}^k$: Mortgage extension by bank $k \in \{\gamma, \delta\}$.
$\bar{\mu}_I^{\gamma}$: Interbank borrowing by bank γ.
d_I^{δ}: Interbank deposits by bank δ.
v_s^h: Effective repayment on mortgage by agent $h \in \{\alpha, \beta\}$ in state $s \in S$.
b_{s1}, b_{s2}: Money spent in the goods and housing markets in state $s \in S^*$.
$\bar{r}^k$: Mortgage rate offered by bank $k \in \{\gamma, \delta\}$.
r_s^k: Short-term loan rate offered by bank $k \in \{\gamma, \delta\}$ in state $s \in S^*$.
$\bar{\mu}_d^{\gamma}$:Amount borrowed from consumers in the form of deposits by bank γ.
m_s^k: Short-term loan extension by bank $k \in \{\gamma, \delta\}$ in state $s \in S^*$.
q_{s1}: Amount of goods offered for sale in state $s \in S^*$.
q_{s2}: Amount of houses offered for sale in state $s \in S^*$.

goods and deposits the rest in the interperiod deposit market. In state 1, when α and β do not default on their mortgages and then find themselves with more housing than they want, they sell some of the amount they bought in the previous period (house prices are high relative to goods prices, and utility maximization leads α and β to switch out of housing into goods).[4] This is possible because the economy is going well, endowments of goods are high, and there is a strong demand for housing from agent λ, a first-time buyer who enters the economy in the second period. Agent ϕ also finds it profitable to sell some of the housing he is left with at those prices.

In state 2, however, Mr. β defaults on his mortgage in period 2 and essentially loses his house, but he still wants to purchase some housing. Although the housing supply is high as a result of the delinquencies, demand from α, β, and λ prevents the price of houses from collapsing. This gives incentives to ϕ to sell some of the housing he owns, as in state 1.

One would expect the same scenario to occur in state 3. However, since both agents α and β become extremely poor in their endowments of goods in that state, their demand for housing drops precipitously. As a result, the housing market should collapse and agent λ, who is the only one endowed with a sufficient amount of the scarce good, should be able to purchase housing at a very low price. The reason that this cannot happen is twofold. First, agent ϕ finds it profitable to purchase back some of the houses he sold in the first period, so both the demand for housing and the price are maintained.[5] The second and most important factor lies in the liquidity constraints that all agents face. In state 3, banks are short of liquidity, so they are only willing to lend money short term at a very high interest rate. Although the good is very expensive, agent λ can only find credit at an extremely high interest rate, which prevents him from enjoying the full benefits of the falling housing market. This is not the case for ϕ as he has money at hand from depositing in the first period.

Finally, lower prices is the last period are outweighed by the high real interest rates. Thus, short-term interest rates rise through the Fisher effect.

4. The agents' cash-in-advance constraints have been adjusted to include housing sales as well as goods sales.

5. Since ϕ does not sell any houses in state 3, he does not demand a short-term loan.

4. Comparative Statics

This section shows the effects of changes in the exogenous variables and parameters of the model. Tables A1 and A2 in the appendix describe the directional effects on endogenous variables of changing various parameters. Although we have performed a number of comparative statics, we discuss in detail only those that we reckon are the most interesting. The analysis involves the following principles, derived from the model structure, on the determination of interest rates, the quantity theory of money, and the Fisher effect.[6]

To determine the interest rate structure, we start with the facts that base money is fiat and the horizon is finite, so in the end no household will be left with fiat money. All households therefore finance their loan repayments to commercial banks via their private cash endowment and the initial capital endowments of banks. However, since we allow for default, the total amount of interest rate repayments is adjusted by the corresponding anticipated default rates. In sum, aggregate ex post interest rate payments, adjusted for default to commercial banks, is equal to the total amount of outside money (that is, sum of cash monetary and initial commercial banks' endowments). In this way, the overall liquidity of the economy and endogenous default codetermine the structure of interest rates.

The model possesses a nonmechanical quantity theory of money. Velocity will always be less than or equal to one (one if all interest rates are positive). However, since the quantities supplied in the markets are chosen by agents (unlike the representative agent model's sell-all assumption), the real velocity of money (that is, how many real transactions can be undertaken by money per unit of time) is endogenous. The upshot of this analysis is that nominal changes (that is, changes in monetary policy) affect both prices and quantities.

Finally, the nominal interest rate is equal to the real interest rate plus the expected rate of inflation.

6. The qualitative structure of the initial equilibrium does not change. For example, an increase in the price of goods in state 3 does not mean that this price has become higher than the prices of goods in states 1 and 2.

4.1 Decrease in the Money Supply

Let the central bank engage in contractionary monetary policy by decreasing the money supply (M^{CB}) in the interbank market in the initial period (or equivalently increasing the interbank interest rate, ρ). The effects on the endogenous variables are summarized in table A1 in the appendix.

Increasing the interbank rate induces bank γ to borrow less from the interbank market and therefore to reduce its supply of short-term loans and mortgages to Mr. α and Mr. ϕ, pushing up the corresponding lending rates, r_0^{γ} and $\bar{r}^{\gamma}$. Consequently, Mr. α reduces his short-term and mortgage borrowing, while Mr. ϕ similarly reduces his short-term borrowing and subsequent deposits in bank γ. Since bank δ increases its deposits in the interbank market, Mr. β faces stricter credit conditions in the short-term. He will therefore switch toward mortgages, which will induce bank δ to reallocate its portfolio and supply slightly more mortgages to him. Finally, from the liquidity structure of interest rates, last period short-term interest rates decrease, except for bank γ in the second state.

Given a higher interest rate, trade becomes less efficient.[7] Quantities of goods and houses traded in the initial period fall, as do prices. We see the quantity theory of money in action in our model. The reduction of the money supply, given that the velocity of money is at most one, typically leads to lower prices and quantities traded. Agent heterogeneity and positive trade volumes are necessary for this result to hold. Given the low price of housing and the increased mortgage extension by bank δ, Mr. β is led to demand more mortgages, which results in a higher mortgage rate ($\bar{r}^{\delta}$) for him, as well. According to the quantity theory of money, since less money chases the same amount of goods, prices will also drop in the last period. Recall that agents default on their mortgages when the value of their housing is less than that of their mortgage. Thus, lower house prices in the second period will result in lower effective returns on the mortgages (which can be interpreted as higher defaults) and even higher initial mortgage rates, given rational expectations. An increase in the interbank rate results not only in increased mortgage extension by the rich bank, but also in lower effective returns (higher levels of effective

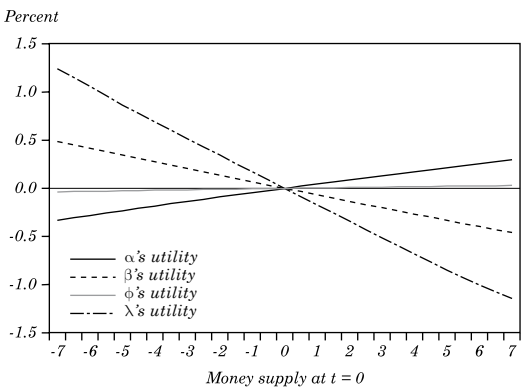
7. The reason is that agents encounter a higher transaction cost.

default) when the bad states materialize. Although the poor bank reduces its mortgage extension, it does not find itself in a better situation, since the effective return on its mortgages also falls when the very bad state obtains.

The higher mortgage extension and mortgage rates for bank δ do not outweigh the lower effective returns stemming from default on mortgages in the bad states of the world (that is, states 2 and 3). The impact on bank γ is the same. Contractionary monetary policy thus results in lower expected profits for the banking sector.

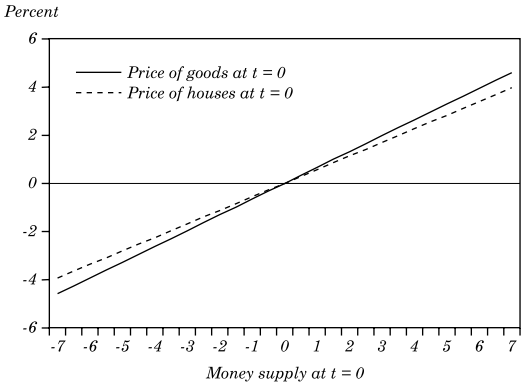
The effect on households differs. For Mr. α, an increase in the interbank rate has a negative effect on his welfare, whereas the opposite holds for Mr. β and Mr. λ. The welfare of Mr. ϕ remains almost unaffected (figure 2). The decrease in α's welfare is mainly due to the fact that he borrows less since he is affiliated with the poor bank. Although the price of housing drops at $t = 0$, the price of goods decreases even more (figure 3). Mr. β is affiliated with the rich bank and undertakes a bigger mortgage to take advantage of the falling housing prices in the initial period. In conjunction with the falling short-term rates in the last period (figure 4), Mr. β's welfare goes up. Mr. λ benefits as well from the lower short-term rates and enjoys an increase in his utility.

Figure 2. Household Welfare versus Money Supply



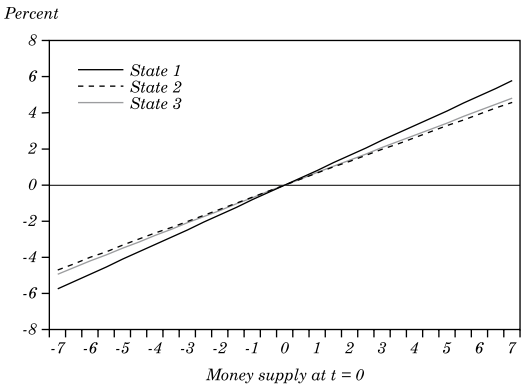
Source: Authors' calculations.

Figure 3. Housing and Goods Prices versus Money Supply



Source: Authors' calculations.

Figure 4. Short-Term Interest Rates by Bank δ versus Money Supply



Source: Authors' calculations.

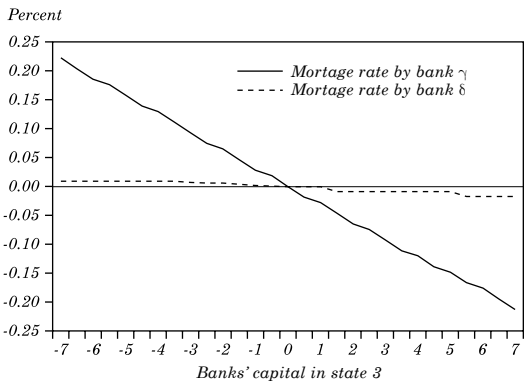
In sum, according to our financial stability measure, contractionary monetary policy results in higher financial instability since lower banking profits and higher default lead to welfare loses in the bad states of nature.

4.2 Liquidity Assistance to Banks in the Very Bad State of the World

Let there be an increase in both banks' capital in the third state of the world, which participants in the economy perfectly anticipate (table A1). This increase can be in the form of liquidity assistance by the government or new equity capital. An increase in the money endowments in the third state of the world will result in a price increase in goods and housing at that state, as expected from the quantity theory of money. A price increase in housing results in a higher effective return for both banks when both Mr. α and Mr. β default on their mortgages. Finding themselves with more money in the very bad state of the world, the banks will increase their extension of mortgages at the initial period. This will drive mortgage rates down and the demand for mortgages up. Bank δ will switch its portfolio from interbank deposits to mortgages, since the latter become less risky. Given the increased activity and higher prices overall, when government help is anticipated in (very) bad states of the world, interest rates in the short loan market rise in the initial period as a result of increased money demand by households.

Although the effective returns on mortgages rises and the overall default rate falls in absolute terms, both banks will sustain a drop in their expected profitability. The reason is that the rates on mortgages to which they switch their portfolios drop (figure 5). In addition,

Figure 5. Mortgage Rates versus Banks' Capital in State 3

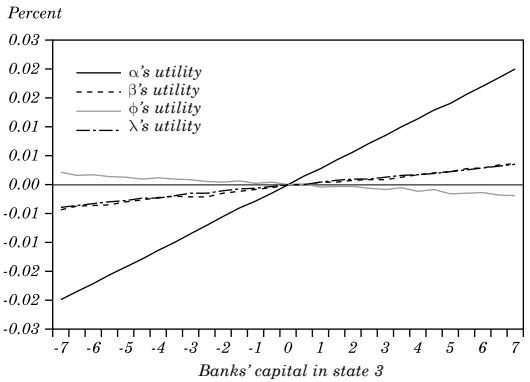


Source: Authors' calculations.

bank γ has to pay a higher interest rate for the money it borrows from depositors and the interbank market, and bank δ does not fully take advantage of the higher interbank rate, since it reallocates its portfolio toward mortgages that obtain higher effective returns.

The welfare of Mr. ϕ decreases because the liquidity injection occurs in state 3, when he is relatively rich, and he suffers a negative wealth effect due to higher prices in that state. Apart from Mr. ϕ, the effect on household welfare is positive (figure 6). Agents α, β, and γ are all better off since the first two benefit from the lower mortgage rates and all three take advantage of lower short-term rates in the last period, which translates into cheaper credit.

Figure 6. Household Welfare versus Banks' Capital in State 3



Source: Authors' calculations.

Liquidity assistance, unlike contractionary monetary policy, not only reduces aggregate default, but also improves the real sector of the economy since it eases credit conditions for households and first-time buyers.

4.3 Banks Become Less Risk Averse

Assume that both banks become more risk loving (see table A2 in the appendix). The change in risk aversion is anticipated in the first period. Their first response will be to switch from safer to riskier investments. Consequently, the extension of mortgages increases and short-term lending decreases, which means lower mortgage rates

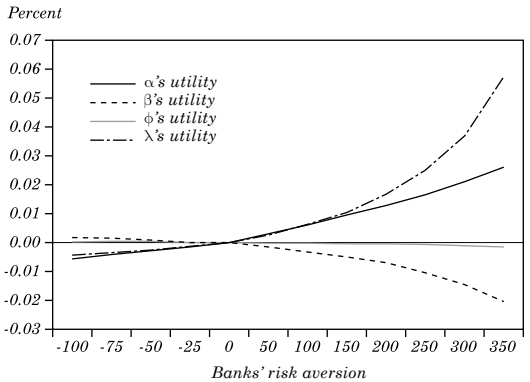
and higher short-term rates in the initial period. Bank δ also reduces its interbank deposits, which results in bank γ having less funds for extending credit. Mr. α takes advantage of the lower mortgage rates and demands more mortgages. He also reduces his sale of goods in the initial period, since he can finance his housing purchases with more mortgages, and the transaction cost of selling his goods (that is, the short-term interest rate) has risen due to the banks' fund reallocation. Mr. β, who is poorly endowed in the initial period, will also reduce his sale of goods and his short-term borrowing. He will not demand more mortgages, however, as the drop in the mortgage rate allows him to maintain his housing purchases. The mortgage rate falls more for Mr. β than for Mr. γ because he is affiliated with bank δ, which has more funds to allocate to mortgages since it reduces its interbank and short-term lending. The demand for housing has increased, but its initial price will fall because Mr. α and Mr. β reduce their initial supply of goods to the market and Mr. ϕ has to sell more of his housing endowment to fund his purchase of goods. Thus, Mr. ϕ's disposable income falls, and he allocates less money to the goods markets, forcing their initial price to drop as well.

Lower housing prices and higher mortgage extension translate into lower effective returns on mortgages because of higher aggregate default in the economy in the bad states. Depending on the severity of the reduction in risk aversion and its initial level, aggregate default may increase a lot. In our exercise, we have chosen a relatively low initial risk aversion (to capture the banks' precrisis risk aversion in the initial equilibrium), so an even a relatively small increase in the appetite for risk results in a 0.5 percent increase in aggregate default. Of course, what matters is the directional effect and not the absolute number. Unlike our other comparative statics, a change in risk aversion, although exogenous in the model, is in reality a choice variable of the banks. The reason that they might adopt a more risk-loving behavior is that they expect higher profits. This is consistent with what our model yields.

Households' welfare moves in different directions (figure 7). Mr. ϕ is better off because houses are a durable commodity and their price should be affected positively by a decrease in the overall risk aversion in the economy. As a result, the price of housing decreases less than the price of goods in the initial period, which generates a slightly positive effect on Mr. ϕ's welfare (see figure 8). Mr. β, who is poorly endowed in the initial period, is also better off, as he benefits from the lower mortgage rates and enjoys an increase in his

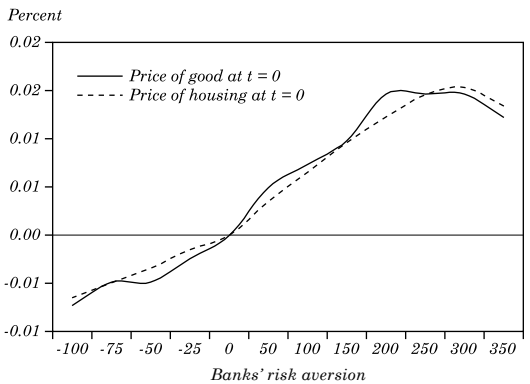
utility. Mr. α, on the other hand, is worse off, since he faces a higher interest rate for short-term loans in the initial period, which is his main source for funding his housing purchases. Mr. λ also sees his welfare decrease because of the rise in short-term interest rates in the last period in response to higher aggregate default (figure 9) and higher real interest rates.

Figure 7. Household Welfare versus Banks' Risk Aversion



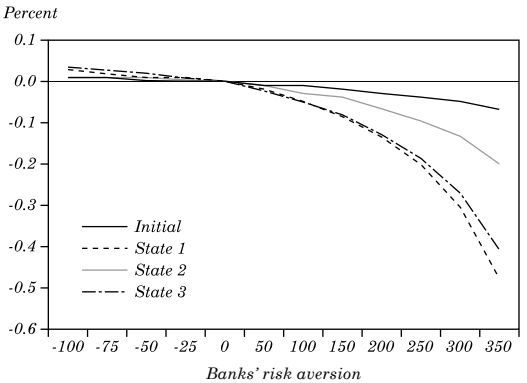
Source: Authors' calculations.

Figure 8. Housing and Goods Prices at $t = 0$ versus Banks' Risk Aversion



Source: Authors' calculations.

Figure 9. Short-Term Interest Rates by Bank δ versus Banks' Risk Aversion



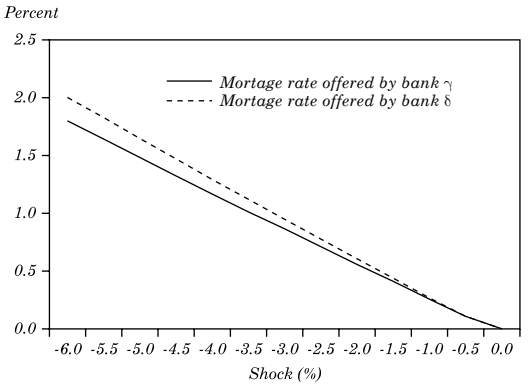
Source: Authors' calculations.

4.4 Compound Comparative Static

The comparative statics we examine above do not fully exhibit what we might expect to observe in a severe mortgage crisis. We therefore performed an exercise of letting more than one adverse shock occur at a time, in which we allow for contractionary monetary policy and a decrease in banks' risk aversion simultaneously. The results are summarize in table A2.

The reduction in the money supply yields a first-order effect that pushes up the interbank rate. Bank δ increases its interbank lending and reduces its mortgage extension. The reduction in risk aversion will moderate this pressure. The trade-off between these two effects will determine whether bank δ will extend more mortgages. In our simulation we find that mortgage extension by bank δ increases. The reduction is more severe for bank γ, since it is more dependent on monetary injections. Mortgage rates rise (figure 10), since demand does not decrease much due to the higher cost of short-term borrowing. Prices of goods and housing fall in all periods and states, as predicted by the quantity theory of money. The pressure is greater due to lower risk aversion (as discussed above). The result is lower expected returns on mortgages, which translate into higher defaults in conjunction with the fact that mortgage rates were higher to start with.

Figure 10. Mortgage Rates versus Compound Decrease in Money Supply and in Banks' Risk Aversion[a]



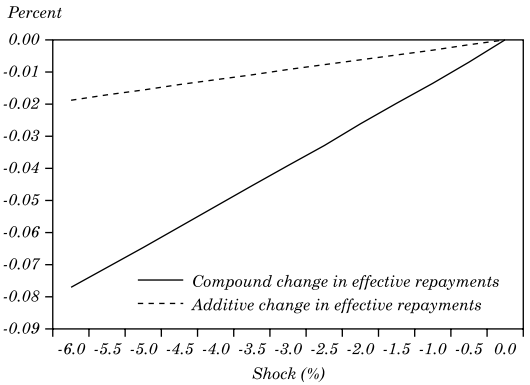
Source: Authors' calculations.
a. More severe shocks are to the left.

Higher default should mean higher mortgage rates, other things being equal, but a higher appetite for risk pushes mortgage rates down. Nevertheless, these second-order effects are outweighed by the increased default resulting from a lower money supply, as analyzed in the relevant section. An interesting result is that default increases disproportionally when contractionary monetary policy is combined with a higher appetite for risk by banks. When these adverse shocks occur at the same time, expected repayment on mortgages falls more than the aggregate change when they happen independently. In particular, nonlinear effects are not trivial, as shown in figure 11.

Expected banking profits go up. On the one hand, the lower money supply and increased default put downward pressure on expected profits, while on the other, lower risk aversion pushes them up. In our exercise, the latter forces prevail, but the effect of the former becomes more intense as the money supply continues to decrease.

The effect on household welfare varies. Agents that are affiliated with the poor bank (that is, Mr. α and Mr. ϕ) observe a decrease in their expected welfare, because the stricter credit environment affects poorly capitalized banks more severely. In addition, the initial price of goods falls more than that of housing (figure 12),

Figure 11. Nonlinear Effects on Mortgage Repayment versus Compound Decrease in Money Supply and in Banks' Risk Aversion[a]



Source: Authors' calculations.
a. More severe shocks are to the left.

Figure 12. Housing and Goods Prices at $t = 0$ versus Compound Decrease in Money Supply and in Banks' Risk Aversion[a]

Source: Authors' calculations.
a. More severe shocks are to the left.

which negatively affects the purchasing power of Mr. α, who mainly finances his housing purchase though the sale of goods in the initial period. Mr. β is able to benefit from the falling housing prices in the initial period by entering a mortgage contract, since he is affiliated with a well capitalized—and more risk-loving—bank, and his welfare increases. Housing prices in state 1 fall more than goods prices (figure 13) because Mr. ϕ decreases his deposits in the initial period and increases his sales of housing in that state to finance the purchase of goods. The lower demand for money by Mr. β in the last period (partially reflecting lower prices and higher defaults) and the well-capitalized position of bank δ put downward pressure on short-term interest rates at the states in which agents default. Mr. λ benefits from the looser credit conditions and enjoys a higher utility.

Figure 13. Housing and Goods Prices in State 1 versus Compound Decrease in Money Supply and in Banks' Risk Aversion[a]

Source: Authors' calculations.
a. More severe shocks are to the left.

However, lower banking profits in the two bad states and the relatively higher aggregate default (relative to contractionary monetary policy only) result in higher welfare losses in these states. Hence, contractionary monetary policy coupled with an attempt to gamble on resurrecting the banks exacerbates the mortgage crisis and increases financial instability.

5. Conclusions

Central bank officials are prone to describe the months since August 2007 as being akin to wartime. In econometric exercises based on longer-run time-series stretching back, say, to 1900, the war years of 1914–18, and 1939–45 are frequently omitted (or dummied out) as involving regimes and structures too atypical for normal analysis. By analogy, the years 2007–08 may also become excluded from standard econometric analysis as too extraordinary to fit with our standard models. After all, such standard models abstract from counterparty risk, from default, from endogenous risk premiums, and even from financial intermediation.

If, however, we want to address and model current events, then we need a model that incorporates default as a central feature and treats credit risk as endogenous (rather than as an exogenous add-on). The model explored above is such a model, albeit an initial, preliminary attempt. Much more needs to be done.

For example, it is an endowment model, so the economy has a given time path of goods, houses, capital, and fiat money. With such predetermined endowments, the resulting time path of prices, interest rates, and quantities just redistributes goods and assets among agents. The welfare implications are never clear-cut since some gain and others lose. To explore the welfare implications of financial crises, they have to be incorporated into a production economy, wherein a credit crunch adversely affects output and employment, so that real incomes become generally reduced and not just redistributed. This can be done and should not be too difficult.

In general, the results of our simulations are more or less what most economists would have imagined. Tight money reduces prices and quantities traded. Government support to banks in crises stabilizes the economy. When banks become risk-loving, a subsequent crisis becomes even more extreme. We are encouraged that our model reproduces common-sense outcomes. The direction of effects seems correct.

This raises the question of whether such a model as this can be taken beyond numerical solution and simulation to the actual data. Could it be used to try to match and calibrate the actual time path of the major data series in existing countries and to explore alternative policy options in real time? We believe that it can, though it will not be straightforward to do so.

Running simulations often provides the analysts with more insight than the readers of the resulting paper. One of the lessons

that this exercise has taught us concerns the limitations of a strict rational expectations model. In a rational expectations model, an event in some subsequent period, such as a change in risk aversion or a change in government policy, may be regarded at the outset as a low probability event, but in a fully rational world it cannot by definition have been entirely unexpected. One cannot run simulations, in a rational expectations world, in which the completely unexpected occurs. This makes it rather harder to simulate extraordinary time periods such as 2007–08. Thus, for example, the risk-seeking behavior of financial intermediaries in 2004–06 gave way to strong risk aversion in 2007–08 in a way that was entirely unexpected in 2004–06. Had it been anticipated, it would have been discounted in a rational expectations system. The solution is to assume that unexpected changes in behavior were actually previously expected, but with an extremely small probability—for example, that there would be a generalized fall in U.S. housing prices. When we started on this exercise, we had not appreciated this. It also raises the philosophical question of whether the subjective probability distribution of actual expectations, based on some combination of the accidents of human history and the limited stretch of our imaginations, can ever approximate the true underlying objective probability distribution. If that approximation is partial at best, in what sense can expectations be held to be rational? Keynes and Shackle would have appreciated that question.

Our purpose, however, is not so much to query the current rational expectations methodology as to demonstrate that within the format of existing best-practice, it should be possible to model a combined collapse of the housing and financial markets.

APPENDIX
Supplemental Tables

We illustrate the results from the comparative statics exercise in two tables. The directional effect of a change in the respective exogenous variables is presented. Other comparative statics we performed include a decrease in liquidity in the short-term loan markets in the last period, a decrease in banks' initial capital, a decrease in banks' capital in the last period, a change in agents' expectations regarding the occurrence of each state of the world, and a production shock in the goods market. The results can be found in our working paper (Goodhart, Tsomocos, and Vardoulakis, 2009).

Table A1. Comparative Statics A

Endogenous variable	*Decrease in money supply at t = 0*	*Liquidity assistance to banks in state 3*	*Endogenous variable*	*Decrease in money supply at t = 0*	*Liquidity assistance to banks in state 3*
p_{01}	−	−	$\bar{d}^{\phi}$	−	+
p_{11}	−	−	μ_0^{ϕ}	−	+
p_{21}	−	−	μ_1^{ϕ}	+	−
p_{31}	−	+	μ_2^{ϕ}	+	−
p_{02}	−	−	μ_1^{λ}	−	−
p_{12}	−	−	μ_2^{λ}	−	−
p_{22}	−	−	μ_3^{λ}	−	+
p_{32}	−	+	q_{01}^{α}	−	−
$\bar{r}^{\gamma}$	+	−	q_{11}^{α}	+	+
$\bar{r}_3^{\gamma}$	−	+	q_{21}^{α}	+	+
$\bar{r}^{\delta}$	+	−	q_{31}^{α}	−	−
$\bar{r}^{\delta}$	−	−	q_{01}^{β}	−	−
$\bar{r}_3^{\delta}$	−	+	q_{11}^{β}	+	+
$\rho, \bar{r}_d, r_0^{\gamma}, r_0^{\delta}$	+	+	q_{21}^{β}	−	−
r_1^{γ}	−	+	q_{31}^{β}	−	+
r_2^{γ}	+	−	b_{01}^{ϕ}	−	−
r_3^{γ}	−	−	b_{11}^{ϕ}	−	−

Table A1. (continued)

Endogenous variable	*Decrease in money supply at t = 0*	*Liquidity assistance to banks in state 3*	*Endogenous variable*	*Decrease in money supply at t = 0*	*Liquidity assistance to banks in state 3*
r_1^{δ}	−	−	b_{21}^{ϕ}	−	−
r_2^{δ}	−	−	b_{31}^{ϕ}	−	+
r_3^{δ}	−	−	q_{11}^{λ}	−	+
$\bar{m}^{\gamma}$	−	+	q_{21}^{λ}	−	−
$\bar{m}^{\delta}$	+	+	q_{31}^{λ}	−	−
m_0^{γ}	−	−	b_{02}^{α}	−	+
m_1^{γ}	+	−	q_{12}^{α}	−	+
m_2^{γ}	+	−	b_{22}^{α}	−	−
m_3^{γ}	+	+	b_{32}^{α}	+	+
m_0^{δ}	−	−	b_{02}^{β}	−	+
m_1^{δ}	+	−	q_{12}^{β}	+	+
m_2^{δ}	+	−	b_{22}^{β}	+	−
m_3^{δ}	−	+	b_{32}^{β}	−	+
$\bar{\mu}_d^{\gamma}$	−	+	q_{02}^{ϕ}	−	+
$\bar{\mu}_I^{\gamma}$	−	+	q_{12}^{ϕ}	+	−
d_I^{δ}	+	−	q_{22}^{ϕ}	+	−
$\bar{\mu}^{\alpha}$	−	+	b_{32}^{ϕ}	−	−
$\bar{\mu}^{\beta}$	+	+	b_{12}^{λ}	+	−
μ_0^{α}	−	−	b_{22}^{λ}	+	−
μ_1^{α}	−	+	b_{32}^{λ}	−	+
μ_2^{α}	−	+	U^{α}	−	+
μ_3^{α}	−	+	U^{β}	+	+
μ_0^{β}	−	−	U^{ϕ}	−	−
μ_1^{β}	−	−	U^{λ}	+	+
μ_2^{β}	−	−	$\gamma's$ profits	−	−
μ_3^{β}	−	+	$\delta's$ profits	−	−

Source: Authors' calculations.

Table A2. Comparative Statics B

Endogenous variable	*Decrease in money supply at t = 0*	*Liquidity assistance to banks in state 3*	*Endogenous variable*	*Decrease in money supply at t = 0*	*Liquidity assistance to banks in state 3*
p_{01}	$-$	$-$	$\bar{d}^{\phi}$	$+$	$-$
p_{11}	$-$	$-$	μ_0^{ϕ}	$+$	$-$
p_{21}	$-$	$-$	μ_1^{ϕ}	$-$	$+$
p_{31}	$-$	$-$	μ_2^{ϕ}	$-$	$+$
p_{02}	$-$	$-$	μ_1^{λ}	$-$	$-$
p_{12}	$-$	$-$	μ_2^{λ}	$-$	$-$
p_{22}	$-$	$-$	μ_3^{λ}	$-$	$-$
p_{32}	$-$	$-$	q_{01}^{α}	$-$	$-$
$\bar{r}^{\gamma}$	$-$	$+$	q_{11}^{α}	$+$	$+$
$\bar{r}_3^{\gamma}$	$-$	$-$	q_{21}^{α}	$+$	$+$
$\bar{r}^{\delta}$	$-$	$+$	q_{31}^{α}	$+$	$+$ *and* $-$
$\bar{r}_2^{\delta}$	$-$	$-$	q_{01}^{β}	$-$	$-$
$\bar{r}_3^{\delta}$	$-$	$-$	q_{11}^{β}	$+$	$+$
$\rho, \bar{r}_d, r_0^{\gamma}, r_0^{\delta}$	$+$	$+$	q_{21}^{β}	$+$	$-$
r_1^{γ}	$-$	$-$	q_{31}^{β}	$-$	$-$
r_2^{γ}	$-$	$+$	b_{01}^{ϕ}	$-$	$-$
r_3^{γ}	$+$	$+$ *and* $-$	b_{11}^{ϕ}	$-$	$-$
r_1^{δ}	$+$	$+$	b_{21}^{ϕ}	$+$	$-$
r_2^{δ}	$+$	$-$	b_{31}^{ϕ}	$-$	$-$
r_3^{δ}	$+$	$-$	q_{11}^{λ}	$+$	$-$
$\bar{m}^{\gamma}$	$+$	$-$	q_{21}^{λ}	$+$	$-$
$\bar{m}^{\delta}$	$+$	$+$	q_{31}^{λ}	$-$	$-$
m_0^{γ}	$-$	$-$	b_{02}^{α}	$+$	$-$
m_1^{γ}	$-$	$+$	q_{12}^{α}	$+$	$+$
m_2^{γ}	$-$	$+$	b_{22}^{α}	$-$	$-$
m_3^{γ}	$-$	$+$ *and* $-$	b_{32}^{α}	$-$	$+$ *and* $-$

Table A2. (continued)

Endogenous variable	*Decrease in money supply at t = 0*	*Liquidity assistance to banks in state 3*	*Endogenous variable*	*Decrease in money supply at t = 0*	*Liquidity assistance to banks in state 3*
m_0^δ	−	−	b_{02}^β	+	−
m_1^δ	−	+	q_{12}^β	+	−
m_2^δ	−	+	b_{22}^β	−	+
m_3^δ	−	−	b_{32}^β	−	−
$\bar{\mu}_d^\gamma$	+	−	q_{02}^ϕ	+	−
$\bar{\mu}_I^\gamma$	+	−	q_{12}^ϕ	−	+
d_I^δ	−	+	q_{22}^ϕ	−	+
$\bar{\mu}^\alpha$	+	−	b_{32}^ϕ	+	−
$\bar{\mu}^\beta$	−	+	b_{12}^λ	−	+
μ_0^α	−	−	b_{22}^λ	−	+
μ_1^α	+	−	b_{32}^λ	−	−
μ_2^α	+	−	U^α	−	−
μ_3^α	+	−	U^β	+	+
μ_0^β	−	−	U^ϕ	+	−
μ_1^β	−	−	U^λ	−	+
μ_2^β	−	−	$\gamma's$ profits	+	+
μ_3^β	−	−	$\delta's$ profits	+	+

Source: Authors' calculations.

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The Balance Sheet Channel

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We study the role of the balance sheet channel of monetary policy in an environment in which credit plays an important role in the funding of new capital investment. Specifically, we ask whether the transmission mechanism of monetary policy is altered in an environment in which financial intermediation with agency costs, aggregate risk on the performance of loans, and banking regulations are all features that can potentially amplify the impact of shocks over the cycle. Because monetary policy has empirically been asymmetric and marked by periods of pronounced action, our approach provides an alternative plausible mechanism that generates the necessary intuition to account for these patterns. Our model is consistent with current New Neoclassical Synthesis models in good times. In bad times (or crisis periods), when systemic losses are potentially large, the model can generate sharp changes in the external finance premium and, therefore, in the patterns of investment.

To illustrate these phenomena, we posit, from first principles, a model with financial intermediation as well as aggregate risk. We articulate a simple characterization of the link between policy and the real economy that passes through leveraged and regulated financial intermediaries to leveraged borrowers, and we then use the model to explore the role of monetary policy and banking regulation. Our model can provide an intuitive, simple, and micro-founded explanation of the financial accelerator. We also show that basic features of banking regulation like deposit reserve requirements or capital adequacy requirements can amplify the cycle by adding to the costs that entrepreneurs have to pay to borrow from the financial system. Hence, that lends some validity to the argument that banking regulation can help mitigate the effects of crises.

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The first-generation New Neoclassical Synthesis models are not well equipped to interpret the role of monetary policy under financial stress, as the recent crisis illustrated. They were based on a couple of classic imperfections, such as nominal rigidities and monopolistic competition, to allow for nontrivial relative price distortions. The goal, of course, was to illustrate how demand shifts could affect real output, and thus how monetary policy shifting nominal demand could have real effects. These models supported an extensive literature on the basic role of monetary policy, but they omitted details of market imperfections that are central to the questions we explore here. We conjecture that these omissions may be partly responsible for the fact that consensus Taylor rules cannot describe the path of monetary policy (Rudebusch, 2006).

A new round of (second-generation) New Neoclassical Synthesis models focuses on the implications of other frictions. Because of the current financial crisis, a huge number of new papers, this one included, have turned their attention to the role of financial and credit market imperfections by building on work by Bernanke, Gertler, and Gilchrist (1999) and Carlstrom and Fuerst (1997, 2001). In particular, there is renewed interest in a real economy link that passes through the banking sector. This channel is now widely believed to play an important role in the conduct of monetary policy. Our question is how and, specifically, how to model it.

A successful model should be able to accomplish a few key tasks. First, it should be able to characterize monetary policy in both normal and crisis periods. Second, it should do so without relying on ad hoc assumptions on the goals of monetary policy. Third, if indeed there is a financial channel or a banks' balance sheet channel, the model should provide an articulation of how this mechanism operates. Of course, the model should do so without sacrificing many of the gains of research to date in characterizing the paths of other aggregates or, crucially, parsimony.

How do we accomplish this? A combination of bank regulation and systemic risk allows us flexibility in a few important ways. First, the presence of systemic risk provides the framework to motivate state-contingent monetary policy that retains the structure of targeting output and inflation explicitly. Second, a fully described regulated banking sector allows us both to maintain the costly state verification (CSV) framework of Townsend (1979), Gale and Hellwig (1985), and Bernanke, Gertler, and Gilchrist (1999) and to introduce the bank lending channel. This provides an answer to

criteria one and three directly. Indeed, we can motivate changes in the pro-inflation response in crisis periods without resorting to ad hoc financial stability targets.

To produce the desired parsimony, we build a variant of the model of Bernanke, Gertler, and Gilchrist (1999) that includes a regulated (but still competitive) banking sector and frictions in the secondary market for used capital. We take this generalization and identify a parsimonious characterization of the external financing premium that intuitively incorporates agency costs due to costly monitoring (costly state verification), as well as the costs of bank regulation on the balance sheet of the financial intermediaries. We show that the external finance premium (EFP) can be represented as follows:

EFP = f (Aggregate Shocks, Agency Cost Channel, Balance Sheet Channel).

We think our approach is useful for two main reasons. First, it reconciles the research agendas that look at stability targeting with those that want a pure monetary policy objective function. Second, it provides a simple and tractable mechanism to explain the financial channel that is consistent both with the banking literature that finds a link between monetary policy and the real economy and with the financial stability literature on the role of capital regulation for monetary policy.[1]

Our approach differs from existing work in a few ways. In one sense, it provides a tractable model through which regulation matters. Unlike models that generate financial channel effects through exogenous spread changes, our model gives an important role to banking intermediation precisely because of the trade-offs present in banking regulation and monetary policy and maintains the view that spreads are at least partly endogenous. Moreover, the model stands on its own because it provides a simple way to think about financial intermediation via leverage and regulatory constraints.

The remainder of the paper is structured as follows. We fully describe the foundations of our model in section 1 and present

1. The literature on this is wide ranging. Bernanke and Lown (1991) argue that the 1992 Basel I deadline contributed to the early 1990s credit crunch, while others suggest that capital regulation generates magnified business cycles. Some relevant papers include Berger and Udell (1994), Blum and Hellwig (1995), Brinkmann and Horvitz (1995), and Thakor (1996). More recent papers include Goodhart, Surinard, and Tsomocos (2006), Estrella (2004), Kashyap and Stein (2004), and Gordy and Howells (2006). See Borio and Zhu (2007) for a comprehensive literature review.

our characterization of the external finance premium in section 2. Moreover, it articulates the intuition of the model for monetary policy and banking regulation. It also discusses a couple of areas for future research, particularly with respect to our characterization of the stance of monetary policy and the banking sector. Section 3 concludes.

1. The Building Blocks of the Model

The financial system is hampered by asymmetries of information between borrowers and lenders and costly state verification, but it is also constrained by regulatory features like capital adequacy and deposit reserve requirements. The economy is populated by a continuum of households and entrepreneurs, each with unit mass. In addition, we include three types of nonfinancial firms (capital goods producers, wholesale producers, and retailers) and one type of financial institution (the banks). All firms, whether financial or nonfinancial, operate under perfect competition, except for the retailers that exploit a monopoly power in their own varieties to add a retail mark-up on their prices. Ownership of all the firms is given to the household, except for wholesale producers who are owned and operated by entrepreneurs.

The banks originate the loans and channel household savings toward the investment needs of the entrepreneurs. The central bank, in turn, has the power to set both banking regulation and monetary policy. Monetary policy is characterized by an interest rate feedback rule in the tradition of Taylor (1993). Banking regulation is summarized in a compulsory reserve requirement ratio on deposits and a capital adequacy requirement on bank capital (or bank equity). The fiscal authority plays a mostly passive role.

In the financial accelerator model of Bernanke, Gertler, and Gilchrist (1999), the relevant friction arises from asymmetric information between entrepreneurs-borrowers and banks-lenders. Monitoring costs make external financing costly for entrepreneurs, so the borrowers' balance sheet conditions play an important role over the business cycle. Otherwise, banks act as a third party inserted between the households and the entrepreneurs whose mission is to intermediate the flow of savings toward investment. In other words, the balance sheet of the lenders that originate the loans becomes passive because loan supply must be equal to the bank deposits demanded by households.

Our benchmark extends the Bernanke-Gertler-Gilchrist model to enhance the role of the banking balance sheet. In particular, we explore the role that banking regulation has on the banks' lending channel and its relevance for monetary policy We also investigate the interaction between banking regulation and monetary policy. We still fit in the tradition of Bernanke, Gertler, and Gilchrist (1999), however, since the basic structure of banking relationships, intermediation, and contract loans is taken as given, rather than arising endogenously, and since we also maintain the illusion of a perfectly competitive banking system. Our model also shares an important characteristic with the framework of Kiyotaki and Moore (1997) in that asset price movements serve to reinforce credit market imperfections.

We depart from Bernanke, Gertler, and Gilchrist (1999) in that banking regulation affects the decisions of banks and, therefore, alters the transmission mechanism in the financial accelerator model. We also depart from their model by introducing systemic (or aggregate) risk on capital income to help us analyze the interest rate spreads, the borrower-lender relationship, and the business cycle dynamics in response to rare or unusual events of large capital income losses.

1.1 Households

There is a continuum of households of unit mass. Households are infinitely lived agents with an identical utility function that is additively separable in consumption, C_t, and labor, H_t. That is,

$$\sum_{\tau=0}^{+\infty} \beta^{\tau} E_t \left[\frac{1}{1-\sigma^{-1}} (C_{t+\tau})^{1-\sigma^{-1}} - \frac{1}{1+\varphi^{-1}} (H_{t+\tau})^{1+\varphi^{-1}} \right], \tag{1}$$

where $0 < \beta < 1$ is the subjective intertemporal discount factor, $\sigma > 0$ ($\sigma \neq 1$) is the elasticity of intertemporal substitution, and $\varphi > 0$ is the Frisch elasticity of labor supply. Households' income comes from renting nonmanagerial labor to the wholesale producers at competitive nominal wages, W_t. It also comes from the ownership of retailers and capital producers, which rebate their total nominal profits (or losses) to them in every period, Π_t^r and Π_t^k, respectively. The unanticipated profits of the banking system are also fully rebated in each period, Π_t^b. Households also obtain their income from interest

on their one-period nominal deposits in the banking system, D_t, and from yields on their stake on bank capital, B_{t+1}. With this disposable income, households finance their aggregate consumption, C_t, open new deposits, D_{t+1}, buy new bank shares, B_{t+1}, and pay their nominal (lump-sum) tax bill, T_t.

Accordingly, the households' sequence of budget constraints is described by

$$P_t C_t + T_t + D_{t+1} + B_{t+1} \leq W_t H_t + I_t D_t + (1-\iota^h) R_t^b B_t + \Pi_t^r + \Pi_t^k + \Pi_t^b, \qquad (2)$$

where I_t is the nominal short-term interest rate offered to depositors, R_t^b is the yield on bank capital, and P_t is the consumer price index (CPI). The nominal tax on bank equity, ι^h, is a convenient simplification to capture the differential tax treatment of capital gains from equity holdings and deposits in many tax codes around the world. As a matter of convention, D_{t+1} and B_{t+1} denote nominal deposits and bank equity held from time t to $t + 1$. Therefore, the interest rate I_{t+1} paid at $t + 1$ is known and determined at time t, but the yield on bank equity R_{t+1}^b could potentially depend on the state of the world at time $t + 1$. Household optimization yields the standard first-order conditions for consumption-savings and labor supply,

$$\frac{1}{I_{t+1}} = \beta E_t \left[\left(\frac{C_{t+1}}{C_t} \right)^{-\sigma^{-1}} \frac{P_t}{P_{t+1}} \right], \qquad (3)$$

$$1 = \beta E_t \left[(1-\iota^h) R_{t+1}^b \left(\frac{C_{t+1}}{C_t} \right)^{-\sigma^{-1}} \frac{P_t}{P_{t+1}} \right], \qquad (4)$$

and

$$\frac{W_t}{P_t} = (C_t)^{\sigma^{-1}} (H_t)^{\varphi^{-1}}, \qquad (5)$$

plus the appropriate no-Ponzi transversality condition. It also implies that each period, budget constraint holds with equality.

As we discuss below, the problem of the banks is such that the yield on bank capital is also known and determined at time t. By simple arbitrage between equations (3) and (4), it follows that (1−

ι^h) $R^b_{t+1} = I_{t+1}$ is necessary for an interior solution to exist (where households hold both bank deposits and bank equity).

1.2 Retailers

There is a continuum of retail firms of unit mass. The retail sector transforms wholesale output into differentiated goods using a linear technology. For simplicity, we assume that no capital or labor is needed in the retail sector, so the wholesale good is the only input of production. Each retail variety is then sold to households, entrepreneurs, and capital goods producers, and bundled up for either consumption or investment (only capital goods producers acquire these varieties for investment purposes). The retailers add a brand name to the wholesale good to introduce differentiation. Variety is valued by all potential consumers, so retailers gain monopolistic power to charge a retail mark-up on them.

1.2.1 Aggregation

We denote the differentiated varieties as $Y_t(z)$, where the index $z \in [0,1]$ identifies each individual retailer. Final goods used for consumption and investment, Y_t, are bundles of these differentiated varieties, $Y_t(z)$, aggregated by means of a common constant elasticity of substitution (CES) index, as follows:

$$Y_t = \left[\int_0^1 Y_t(z)^{\frac{\theta-1}{\theta}} dz \right]^{\frac{\theta}{\theta-1}}. \tag{6}$$

The elasticity of substitution across varieties is represented by $\theta > 1$. The corresponding consumption price index (CPI) is given by

$$P_t = \left[\int_0^1 P_t(z)^{1-\theta} dz \right]^{\frac{1}{1-\theta}}, \tag{7}$$

where $P_t(z)$ is the price charged by retailer z for its variety. The optimal allocation of expenditure to each variety, that is,

$$Y_t(z) = \left[\frac{P_t(z)}{P_t} \right]^{-\theta} Y_t, \tag{8}$$

implies that retailers face a downward-sloping demand function.

1.2.2 Optimal pricing

Retailers set prices to maximize profits, but their ability to reoptimize is constrained because they face nominal rigidities à la Calvo (1983). The retailer maintains its previous period price with an exogenous probability $0 < \alpha < 1$ in each period. However, with probability $(1 - \alpha)$, the retailer is allowed to optimally reset its price. Whenever reoptimization is possible, a retailer z chooses its price, $\tilde{P}_t(z)$, to maximize the expected discounted value of its net nominal profits, that is,

$$\sum_{\tau=0}^{+\infty} E_t \left\{ \alpha^{\tau} M_{t,t+\tau} \tilde{Y}_{t,t+\tau}(z) \left[\tilde{P}_t(z) - (1-\iota^r) P^w_{t+\tau} \right] \right\}, \tag{9}$$

where

$$M_{t,t+\tau} \equiv \beta^{\tau} \left(\frac{C_{t+\tau}}{C_t} \right)^{-\sigma^{-1}} \frac{P_t}{P_{t+\tau}},$$

is the household's stochastic discount factor (SDF) for τ-periods-ahead nominal payoffs, $P^w_{t+\tau}$ is the nominal price of wholesale goods, and

$$\tilde{Y}_{t,t+\tau}(z) = \left[\frac{\tilde{P}_t(z)}{P_{t+\tau}} \right]^{-\theta} Y_{t+\tau},$$

is the demand at time $t + \tau$ given that prices remain fixed at $\tilde{P}_t(z)$ (see equation 8). We also include a subsidy on inputs for retailers, ι^r, which is used by the government to eliminate the retail mark-up distortion whenever $\iota^r = 1/\theta$.

The solution to the retailer's maximization problem satisfies the following first-order condition:

$$\sum_{\tau=0}^{+\infty} E_t \left\{ (\alpha\beta)^{\tau} \left(\frac{C_{t+\tau}}{C_t} \right)^{-\sigma^{-1}} \tilde{Y}_{t,t+\tau}(z) \left[\frac{\tilde{P}_t(z)}{P_{t+\tau}} - \frac{\theta(1-\iota^r)}{\theta - 1} \frac{P^w_{t+\tau}}{P_{t+\tau}} \right] \right\} = 0, \tag{10}$$

where $\theta/(\theta - 1)$ denotes the retail mark-up, and P^w_t/P_t denotes the price of wholesale output in units of consumption. The latter provides a measure for the real marginal costs before the government subsidy. The first-order condition in equation (10) is often referred to as the price-setting rule. Given that a fraction α of retailers maintains prices in period t and

that all reoptimizing retailers face a symmetric problem, the aggregate CPI in equation (7) can be rewritten in the following terms:

$$P_t = \left[\alpha P_{t-1}^{1-\theta} + (1-\alpha)\tilde{P}_t\ (z)^{1-\theta}\right]^{\frac{1}{1-\theta}}, \tag{11}$$

where $\tilde{P}_t(z)$ is the (symmetric) optimal price implied by equation (10).

Technically, there is no aggregate production function for the final output, Y_t. However, there is a simple way to account for the distribution of resources. By market clearing, the sum of the individual retailers' demands of the wholesale good has to be equal to the total production of the wholesale producers, that is,

$$\int_0^1 Y_t(z)dz = Y_t^w. \tag{12}$$

Using the optimal allocation of expenditure in equation (8), we get

$$Y_t = \left(\frac{P_t^*}{P_t}\right)^{\theta} Y_t^w, \tag{13}$$

where

$$P_t^* \equiv \left[\int_0^1 P_t(z)^{-\theta} dz\right]^{-\frac{1}{\theta}} = \left[\alpha(P_{t-1}^*)^{-\theta} + (1-\alpha)\tilde{P}_t(z)^{-\theta}\right]^{-\frac{1}{\theta}}. \tag{14}$$

The term $p_t^* \equiv (P_t^* / P_t)^{\theta} \leq 1$ characterizes the magnitude of the efficiency distortion due to sticky prices.

Since households own the retailers, we assume that all profits (or losses) from the retail activity are rebated to the households as a lump sum in every period. After a bit of algebra, the aggregate nominal profits received by the households can be computed as

$$\begin{aligned} \Pi_t^r &= \int_0^1 \left\{ Y_t(z)\left[P_t(z) - (1-\iota^r)P_t^w\right] dz \right\} \\ &= P_t \left(\frac{P_t^*}{P_t}\right)^{\theta} Y_t^w - (1-\iota^r)P_t^w Y_t^w, \end{aligned} \tag{15}$$

where the second equality follows from the optimal allocation of expenditure in each variety described in equation (8), the aggregation formulas in equations (6) and (7), and the relationship between final output and wholesale output implied by equation (12).

1.3 Capital Goods Producers

There is a continuum of capital goods producers of unit mass. At time t, these producers combine aggregate investment goods, X_t, and depreciated capital, $(1-\delta)K_t$, to manufacture new capital goods, K_{t+1}. The production of new capital is limited by technological constraints. We assume that the aggregate stock of new capital evolves according to the following law of motion:

$$K_{t+1} \leq (1-\delta)K_t + \Phi\,(X_t, X_{t-1}, K_t)\,X_t, \tag{16}$$

where X_t is real aggregate investment, K_t stands for real aggregate capital, and $0 < \delta < 1$ is the depreciation rate. The function $\Phi(X_t, X_{t-1}, K_t)$ implicitly characterizes the technology available to the capital goods producers to transform investment goods into new capital.

We explore three different specifications of the technological constraint. The neoclassical adjustment case (NAC) assumes that the transformation of investment goods into new capital can be attained at a one-to-one rate:

$$\Phi\,(X_t, X_{t-1}, K_t) = 1. \tag{17}$$

The specification for the so-called capital adjustment case (CAC), favored by Bernanke, Gertler, and Gilchrist (1999) and others, takes the following form:

$$\Phi\left(\frac{X_t}{K_t}\right) = 1 - \frac{1}{2}\chi\frac{\left[(X_t/K_t)-\delta\right]^2}{(X_t/K_t)}, \tag{18}$$

where X_t/K_t denotes the investment-to-capital ratio. Finally, the investment adjustment case (IAC), preferred by Christiano, Eichenbaum, and Evans (2005) takes the following form:

$$\Phi\left(\frac{X_t}{X_{t-1}}\right) = 1 - \frac{1}{2}\kappa\frac{\left[(X_t/X_{t-1})-1\right]^2}{(X_t/X_{t-1})}, \tag{19}$$

where X_t/X_{t-1} denotes the gross investment growth rate. The parameters $\chi > 0$ and $\kappa > 0$ regulate the degree of concavity of the technological constraint and, therefore, the sensitivity of investment in new capital. In steady state, the CAC function satisfies that $\Phi(\delta) = 1$, $\Phi'(\delta) = 0$, and $\Phi''(\delta) = -(\chi/\delta) < 0$. Similarly, the IAC function satisfies that $\Phi(1) = 1$, $\Phi'(1) = 0$, and $\Phi''(1) = -\kappa < 0$.

Capital goods producers choose their investment demand, X_t, and their output of new capital, K_{t+1}, to maximize the expected discounted value of their net profits:

$$\sum_{\tau=0}^{+\infty} E_t \left\{ M_{t,t+\tau} P_{t+\tau} \left[Q_{t+\tau} K_{t+\tau+1} - (1-\delta) \bar{Q}_{t+\tau} K_{t+\tau} - X_{t+\tau} \right] \right\}, \tag{20}$$

subject to the law of motion for capital described in equation (16). Here,

$$M_{t,t+\tau} \equiv \beta^{\tau} \left(\frac{C_{t+\tau}}{C_t} \right)^{-\sigma^{-1}} \frac{P_t}{P_{t+\tau}},$$

is the household's stochastic discount factor for τ-periods-ahead nominal payoffs, since households own the capital goods producers. As a matter of convention, K_{t+1} denotes the real stock of capital built (and determined) at time t for use at time $t + 1$.

The investment good is bundled in the same fashion as the consumption good and is bought at the same price, P_t. The depreciated capital is bought at a resale price, $\bar{Q}_t$, in units of the consumption good. However, the new capital is sold to the entrepreneurs at a price Q_t, which determines the relative cost of investment in unit of consumption and is often referred to as Tobin's Q. We assume that frictions in the secondary market for used capital prevent arbitrage between the resale value of old capital and the sale value of new capital, that is, $\bar{Q}_t = o_t Q_t$ where $o_t \neq 1$. Those frictions are left unmodeled, although we also assume that the parties involved in the secondary market (namely, entrepreneurs and capital goods producers) view them as entirely out of their control. Hence, they treat the wedge, o_t, as an exogenous and random shock.

Moreover, there is no centralized market that ensures a uniform pricing for used capital, so each individual entrepreneur and capital producer pair matched in the secondary market gets a different draw of this random wedge. In other words, o_t is modeled not as an aggregate shock, but as an idiosyncratic one. Nonetheless, we map this resale shock into the Bernanke-Gertler-Gilchrist framework as closely as possible. That keeps our departure from their model to a minimum, but requires us to note that the wedge, o_t , has a component that depends on other endogenous variables that have an influence on the capital returns that the entrepreneurs can generate.

The optimization of the capital goods producers yields a standard first-order condition that determines the linkage between Tobin's Q, Q_t, and investment, X_t, that is,

$$\begin{aligned} &Q_t\left[\Phi(X_t,X_{t+1},K_t)+\frac{\partial\Phi(X_t,X_{t-1},K_t)}{\partial X_t}X_t\right] \\ &+\beta\left[\left(\frac{C_{t+1}}{C_t}\right)^{-\sigma^{-1}}Q_{t+1}\frac{\partial\Phi(X_{t+1},X_t,K_{t+1})}{\partial X_t}X_{t+1}\right]=1, \end{aligned} \tag{21}$$

which does not depend on the wedge, o_t. The law of motion for capital is binding in each period. Given our alternative specifications of the technological constraint, we could rewrite the first-order condition in equation (21) more compactly as follows:

$$\begin{cases} Q_t=1, \quad \text{if NAC;} \\ Q_t\left[\Phi\left(\frac{X_t}{K_t}\right)+\Phi'\left(\frac{X_t}{K_t}\right)\frac{X_t}{K_t}\right]=1, \quad \text{if CAC;} \\ Q_t\left[\Phi\left(\frac{X_t}{X_{t-1}}\right)+\Phi'\left(\frac{X_t}{X_{t-1}}\right)\frac{X_t}{X_{t-1}}\right]=1+\beta\left[\left(\frac{C_{t+1}}{C_t}\right)^{-\sigma^{-1}}Q_{t+1}\Phi'\left(\frac{X_{t+1}}{X_t}\right)\left(\frac{X_{t+1}}{X_t}\right)^2\right], \text{ if IAC.} \end{cases} \tag{22}$$

The neoclassical adjustment case is of particular interest because without the asset price fluctuations captured by Tobin's Q, the Bernanke-Gertler-Gilchrist framework loses the characteristic that asset price movements serve to reinforce credit market imperfections. For more details on the derivations of the Tobin's Q equations, see Martínez-García and Sondergaard (2008).

Profits (or losses) may arise since X_{t-1} and K_t are predetermined at time t and cannot be adjusted freely. The aggregate profits at each point in time for the capital goods producers, that is,

$$\begin{aligned} \prod_t^k &\equiv P_tQ_tK_{t+1}-(1-\delta)P_t\left[\int_0^1\overline{Q}_t\mu_t^o(o_t)\,do_t\right]K_t-P_tX_t \\ &=P_tQ_t\Phi(X_t,X_{t-1},K_t)X_t-\left[\int_0^1 o_t\mu_t^o(o_t)\,do_t-1\right](1-\delta)P_tQ_tK_t-P_tX_t, \end{aligned} \tag{23}$$

must be added to the households' budget constraint (since households are their only shareholders). Here, $\mu_t^o(o_t)$ denotes the mass of capital goods producers receiving a given realization of the idiosyncratic shock, o_t.

1.4 Wholesale Producers

There is a continuum of mass one of wholesale producers. Wholesale producers combine the nonmanagerial labor provided by the households with the managerial labor supplied and the capital rented from the entrepreneurs to produce wholesale goods according to the following Cobb-Douglas technology:

$$Y_t^w \leq e^{a_t}(K_t)^{1-\psi-\varsigma}(H_t)^{\psi}(K_t^e)^{\varsigma}\ , \tag{24}$$

where Y_t^w is the output of wholesale goods, K_t is the aggregate capital rented, and H_t and H_t^e are the demands for nonmanagerial and managerial labor, respectively.

With a constant returns-to-scale technology, the nonmanagerial and managerial labor shares in the production function are determined by the coefficients $0 < \psi < 1$ and $0 < \varsigma < 1$. In keeping with Bernanke, Gertler, and Gilchrist (1999), the managerial share is often assumed to be very small, that is, ς would be close to zero. The productivity shock, a_t, allows a first-order autoregressive, or AR(1), process of the following form:

$$a_t = \zeta_a a_{t-1} + \varepsilon_t^a, \tag{25}$$

where ε_t^a is a zero mean, uncorrelated, and normally distributed innovation. The parameter $-1 < \zeta_a < 1$ determines the persistence of the productivity shock, and $\sigma_a^2 > 0$ the volatility of its innovation.

Wholesale producers maximize their static profit:

$$\prod_t^w \equiv P_t^w Y_t^w - R_t^w K_t - W_t H_t - W_t^e H_t^e, \tag{26}$$

subject to the technological constraint implied by equation (24). Wholesale producers rent labor from households and entrepreneurs at competitive nominal wages W_t and W_t^e, respectively, and they compensate the entrepreneurs with a nominal return per unit of capital rented, R_t^w. The optimization of the wholesale producers results in the following well-known rules to compensate the factors of production:

$$R_t^w = (1-\psi-\zeta)\frac{P_t^w Y_t^w}{K_t}; \tag{27}$$

$$W_t = \psi\frac{P_t^w Y_t^w}{H_t}; \tag{28}$$

$$W_t^e = \zeta\frac{P_t^w Y_t^w}{H_t^e}. \tag{29}$$

The optimization of the wholesale producer can be summarized in these first-order conditions plus the technological constraint in equation (24) holding with equality. Wholesale producers make zero profits in every period (that is, $\Pi_t^w=0$), so the entrepreneurs who own them do not receive any dividends. All the income entrepreneurs extract comes from their supply of two key inputs in the production function—managerial labor and, especially, capital. Wholesale producers rent the capital they use from the entrepreneurs and return the depreciated capital after production has taken place.

As we discuss shortly, uncertainty about the resale value of depreciated capital is the underlying risk that distorts the relationship between borrowers (the entrepreneurs) and lenders (the banks). In fact, asymmetries of information on this type of risk and costly state verification lead to a distorted allocation of households' savings toward the productive capital investments operated by the entrepreneurs.

1.5 Entrepreneurs

There is a continuum of entrepreneurs of unit mass. Entrepreneurs are infinitely lived agents with identical preferences that are linear in consumption, C_t^e:

$$\sum\nolimits_{\tau=0}^{\infty}(\beta\eta)^{\tau} E_t\left(C_{t+\tau}^e\right), \tag{30}$$

where $0 < \beta\eta < 1$ is the subjective intertemporal discount factor. Entrepreneurs inelastically supply one unit of managerial labor:

$$H_t^e = 1, \quad \forall t. \tag{31}$$

The entrepreneurs' utility function also differs from that of the households because they are risk neutral (linear utility), and they discount utility at a higher rate (that is, $0 < \eta < 1$). The relative impatience is intended to ensure that entrepreneurs never save enough resources to overcome their financing constraints. The assumption of risk neutrality implies that entrepreneurs care only about expected returns, which considerably simplifies the financial contract (see the appendix).

At the end of period t, the entrepreneur receives a competitive nominal wage, W_t^e, and earns income from the capital rented at the beginning of the period for the production of wholesale goods, $R_t^w K_t$, as well as from the resale value on the depreciated capital bought by the capital goods producers, $(1-\delta)P_t\bar{Q}_t K_t$.[2] After repaying their outstanding

2. Distortions in the secondary market create a random wedge between the acquisition cost of new capital and the resale value of old capital in each period.

loans to the banking system, L_t, entrepreneurs can appropriate a fraction of the aggregate capital income, that is, a share of $R_t^w K_t + (1-\delta)P_t\bar{Q}_t K_t$. The entrepreneurs own the wholesale producers, but these firms generate zero profits after paying for the factors of production and, therefore, produce no dividends for the entrepreneurs.

Using the resources coming from managerial wages and capital rental rates, the entrepreneurs must buy the new capital, K_{t+1}, and decide how much to consume, C_t^e. New capital is needed for the production of wholesale goods at time $t + 1$. Net of consumption, the entrepreneurs set aside a portion of their income in the form of entrepreneurial net worth, N_{t+1}. Entrepreneurial net worth is, in effect, a form of savings for the entrepreneur that can be applied partly to acquire new capital. The entrepreneurs use these savings, N_{t+1}, as well as external loans from the banking system, L_{t+1}, to fund the acquisition of the entire stock of new capital, $P_t Q_t K_{t+1}$:

$$P_t Q_t K_{t+1} = N_{t+1} + L_{t+1}. \tag{32}$$

Equation (32) also implies that new capital is the only asset in which entrepreneurs can invest their savings. As in Bernanke, Gertler, and Gilchrist (1999), we rule out a more complex portfolio setting for entrepreneurs.

1.5.1 Idiosyncratic and anticipated systemic risk

We define the returns on capital relative to its acquisition cost whenever the resale value of capital and the cost of new capital are equalized as

$$R_t^e \equiv \frac{R_t^w K_t + (1-\delta)P_t Q_t K_t}{P_{t-1} Q_{t-1} K_t}.$$

For an individual entrepreneur, we define the returns on the capital that was acquired at time $t - 1$, $\omega_t R_t^e$, as the total income generated by a unit of capital at time t after accounting for the effects of the distortion in the secondary market:[3]

3. To be more precise, we define the rate of return on capital, R_t^e, as the rate that would prevail if the secondary market for used or depreciated capital led to arbitrage between the resale value of capital and the cost of acquiring new capital, that is, $\bar{Q}_t = Q_t$. The returns on capital are realized under distortions in the secondary market, so the actual rate of return on capital is $\omega_t R_t^e$, as defined in equation (33). For convenience, we implicitly capture the randomness of the wedge in the resale value, o_t, by positing that ω_t is a purely exogenous random variable.

$$\omega_t R_t^e \equiv \frac{R_t^w K_t + (1-\delta) P_t \bar{Q}_t K_t}{P_{t-1} Q_{t-1} K_t} = \left[\frac{(R_t^w / P_t) + (1-\delta) o_t Q_t}{Q_{t-1}} \right] \frac{P_t}{P_{t-1}}, \tag{33}$$

where the rental rate on capital, R_t^w, is defined in equation (27). Returns on capital are subject to idiosyncratic shocks, ω_t, which reflect the impact of the random resale distortion:

$$o_t \equiv O\left(\omega_t, \frac{R_t^w}{P_t Q_t}\right).$$

The function that links the wedge on the secondary market, o_t, to the idiosyncratic shock, ω_t, can be expressed as

$$\begin{aligned} o_t \equiv O\left(\omega_t, \frac{R_t^w}{P_t Q_t}\right) &= \frac{\omega_t R_t^e P_{t-1} Q_{t-1} K_t - R_t^w K_t}{(1-\delta) P_t Q_t K_t} \\ &= \omega_t + (\omega_t - 1) \frac{R_t^w}{(1-\delta) P_t Q_t}, \end{aligned} \tag{34}$$

where the second equality follows from the definition of R_t^e.

We interpret the shock $\omega_{t+1} \in (0, +\infty)$ as a reduced-form representation of the exogenous losses on the resale value of the depreciated capital due to frictions in the secondary market. Those frictions, which are left unmodeled, imply a wedge between the resale value of capital and the acquisition cost of new capital (of Tobin's Q) within the period. We denote $\phi(\omega_{t+1} | s_{t+1})$ the density and $\Phi(\omega_{t+1} | s_{t+1})$ the cumulative distribution of ω_{t+1} conditional on a given realization of the aggregate shock s_{t+1}.

We assume that the expected capital return of each entrepreneur is a function of the aggregate shock s_{t+1} (for example, Faia and Monacelli, 2007). The aggregate shock s_{t+1} captures our notion of systemic risk on the resale value of depreciated capital, which has the effect of shifting the mean of the distribution of the risky capital returns. The systemic risk shock, s_t, follows an AR(1) process of the following form:

$$s_t = \rho_s s_{t-1} + \varepsilon_t^s, \tag{35}$$

where ε_t^s is a zero mean, uncorrelated, and normally distributed innovation. The parameter $-1 < \rho_s < 1$ determines the persistence of the systemic shock, and $\sigma_s^2 > 0$ the volatility of its innovation.

We assume that the realization of the time $t + 1$ shock is publicly observed at time t. Therefore, these systemic shocks are interpreted as anticipated (rather than unanticipated) losses.

The expected idiosyncratic shock on capital income, ω_{t+1}, conditional on the realization of the aggregate shock, s_{t+1}, is given by

$$E_t(\omega_{t+1}|s_{t+1}) = 1 - J(s_{t+1}), \tag{36}$$

where $0 \leq \lambda \equiv J(0) < 1$ determines the level of the expected losses in steady state, and $-\infty < \xi \equiv J'(0) < +\infty$ characterizes the sensitivity of the expected losses. This specification is flexible enough to allow for catastrophic losses due to a sizeable systemic risk shock s_{t+1}. By choosing λ sufficiently close to zero, we ensure that the expected idiosyncratic shock remains relatively close to one most of the time, that is, $E_t(\omega_{t+1}|s_{t+1}) \cong 1$. That means that entrepreneurs get, on average, a capital return that is approximately equal to R_t^e, which is what is expected whenever the acquisition cost and the resale value of capital are equalized within each period.[4]

1.5.2 The loan contract

At time t, the entrepreneurs-borrowers and the banks-lenders must agree on a contract that facilitates the acquisition of new capital,

4. Given the characterization of the idiosyncratic shock ω_t in equation (33) and the definition of the capital return under equalization between the resale value of capital and the acquisition cost, R_t^e, we can argue that the expected or average value of depreciated capital is equal to

$$\begin{aligned}(1-\delta)P_tQ_tK_t\left[\int_0^1 o_t\mu_t^o(o_t)do_t\right] &= \left[\int_0^{+\infty}\omega_t\phi(\omega_t \mid s_t)d\omega_t - 1\right]R_t^w K_t \\ &+ \left[\int_0^{+\infty}\omega_t\phi(\omega_t \mid s_t)d\omega_t\right](1-\delta)P_tQ_tK_t \\ &= (1-\delta)P_tQ_tK_t - J(s_t)\left[R_t^w K_t + (1-\delta)P_tQ_tK_t\right] \\ &= (1-\delta)P_tQ_tK_t - P_{t-1}Q_{t-1}K_tR_t^eJ(s_t),\end{aligned}$$

where we use the fact that $1 - J(s_t)$ is the expectation of ω_t. Given this, we can rewrite the aggregate profits for the capital goods producers in equation (23) as

$$\begin{aligned}\Pi_t^k &= P_tQ_tK_{t+1} - (1-\delta)P_tQ_tK_t - P_tX_t + (1-\delta)P_tQ_tK_t\left[1 - \int_0^1 o_t\mu_t^o(o_t)\,do_t\right] \\ &= P_tQ_tK_{t+1} - (1-\delta)P_tQ_tK_t - P_tX_t + P_{t-1}Q_{t-1}K_tR_t^eJ(s_t).\end{aligned}$$

We can see from this aggregate profit function that what we call systemic losses for the entrepreneur are additional profits for the capital goods producers.

K_{t+1}, and that has to be repaid at time $t + 1$. The entrepreneurs operate in a legal environment that ensures them limited liability. Hence, in case of default at time $t + 1$, the banks can only appropriate the total capital return of the entrepreneur at time $t + 1$, that is, $\omega_{t+1}R^e_{t+1}P_tQ_tK_{t+1}$. The loan is restricted to take the standard form of a one-period risky debt contract as in Townsend (1979), Gale and Hellwig (1985), and Bernanke, Gertler, and Gilchrist (1999).[5]

We assume that the idiosyncratic shock ω_{t+1} is not known at time t when the loan contract is signed, and that the realization of the idiosyncratic shock can only be observed privately by the entrepreneurs himself at time $t + 1$. Banks, however, observe the systemic shock s_{t+1} at time t and have access to a costly monitoring technology that permits them to uncover the true realization of the idiosyncratic shock ω_{t+1} at a cost, that is, at a cost of $\mu\omega_{t+1}R^e_{t+1}P_tQ_tK_{t+1}$, where $0 < \mu < 1$.

Default on a loan signed at time t occurs whenever the capital returns obtained by the entrepreneur at time $t + 1$ after the realization of the idiosyncratic shock ω_{t+1}, that is $\omega_{t+1}R^e_{t+1}P_tQ_tK_{t+1}$, fall short of the amount that needs to be repaid. Hence the default space is implicitly characterized by

$$\omega_{t+1}R^e_{t+1}P_tQ_tK_{t+1} \leq I^l_{t+1}L_{t+1}, \tag{37}$$

where I^l_{t+1} is short-hand notation for the repayment amount agreed at time t per unit of loan, and L_{t+1} represents the loan size. A risky one-period loan contract at time t can be defined in terms of a threshold on the idiosyncratic shock, $\bar{\omega}_t$, and a measure of capital returns, $R^e_{t+1}P_tQ_tK_{t+1}$, such that the repayment is equal to

$$I^l_{t+1}L_{t+1} = \bar{\omega}_{t+1}R^e_{t+1}P_tQ_tK_{t+1}. \tag{38}$$

Given the terms of the loan contract, the lenders will commit to supply as much external funding as the entrepreneurs choose to demand under those conditions. Another way to interpret the implication of equations (37) and (38) is that making a loan to the entrepreneurs entitles the lenders to share in their capital returns.

When default occurs, that is, when $\omega_t < \bar{\omega}_t$, the entrepreneur

5. For a discussion of optimal contracts in a dynamic costly state verification framework, see Monnet and Quintin (2005).

cannot repay the amount it owed based on the capital returns derived from investment. To avoid misreporting on the part of defaulting entrepreneurs, the lender must verify the individual entrepreneur's income statement. That requires the lender to expend resources by an amount of $\mu\omega_{t+1}R^e_{t+1}P_tQ_tK_{t+1}$ in monitoring costs. In case of default, the lender always chooses to monitor and the entrepreneur gets nothing, while the bank appropriates $(1-\mu)\omega_{t+1}R^e_{t+1}P_tQ_tK_{t+1}$ for itself. If the entrepreneur does not default, that is, if $\omega_t > \bar{\omega}_t$, then the entrepreneur pays $\bar{\omega}_{t+1}R^e_{t+1}P_tQ_tK_{t+1}$ back to the lender and keeps the rest for himself. In other words, the entrepreneur gets to keep $(\omega_{t+1} - \bar{\omega}_{t+1})R^e_{t+1}P_tQ_tK_{t+1}$.

We take this defaulting rule and the implied sharing agreement of capital returns between the entrepreneur-borrower and the bank-lender as given. At time $t + 1$, the capital returns net of borrowing costs expected by the entrepreneurs after observing all aggregate shocks, but before the realization of its own idiosyncratic shock ω_{t+1}, can be computed as follows:[6]

$$\begin{aligned}
&\int_{\bar{\omega}_{t+1}}^{+\infty}\left[\omega_{t+1}R^e_{t+1}P_tQ_tK_{t+1} - I^l_{t+1}L_{t+1}\right]\phi(\omega_{t+1} \mid s_{t+1})d\omega_{t+1} \\
&\quad = R^e_{t+1}P_tQ_tK_{t+1}\left[\int_{\bar{\omega}_{t+1}}^{+\infty}(\omega_{t+1} - \bar{\omega}_{t+1})\phi(\omega_{t+1} \mid s_{t+1})d\omega_{t+1}\right] \qquad (39) \\
&\quad = R^e_{t+1}P_tQ_tK_{t+1}f(\bar{\omega}_{t+1}, s_{t+1}),
\end{aligned}$$

where

$$f(\bar{\omega}_{t+1}, s_{t+1}) \equiv \int_{\bar{\omega}_{t+1}}^{+\infty}\omega_{t+1}\phi(\omega_{t+1}|s_{t+1})d\omega_{t+1} - \bar{\omega}_{t+1}\left[1 - \Phi(\bar{\omega}_{t+1}|s_{t+1})\right]. \qquad (40)$$

By the law of large numbers, equation (40) can be interpreted also as the fraction of the expected capital return obtained by the average entrepreneur. In a similar fashion, the capital returns net of monitoring costs expected by the lenders after observing all aggregate shocks at time $t + 1$ would be equal to

$$\begin{aligned}
&(1-\mu)\int_0^{\bar{\omega}_{t+1}}\left[\omega_{t+1}R^e_tP_tQ_tK_{t+1}\right]\phi(\omega_{t+1}|s_{t+1})d\omega_{t+1} + \int_{\bar{\omega}_{t+1}}^{+\infty}\left[I^l_{t+1}L_{t+1}\right]\phi(\omega_{t+1}|s_{t+1})d\omega_{t+1} \\
&\quad = R^e_{t+1}P_tQ_tK_{t+1}\left[(1-\mu)\int_0^{\bar{\omega}_{t+1}}\omega_{t+1}\phi(\omega_{t+1}|s_{t+1})d\omega_{t+1} + \bar{\omega}_{t+1}\int_{\bar{\omega}_{t+1}}^{+\infty}\phi(\omega_{t+1}|s_{t+1})d\omega_{t+1}\right] \qquad (41) \\
&\quad = R^e_{t+1}P_tQ_tK_{t+1}g(\omega_{t+1}, s_{t+1}),
\end{aligned}$$

6. Here, aggregate shocks includes the productivity shocks, a_{t+1}, the monetary shock, m_{t+1}, and the systemic risk shocks, s_{t+1}.

where

$$g(\bar{\omega}_{t+1}, s_{t+1}) \equiv (1-\mu)\int_0^{\bar{\omega}_{t+1}} \omega_{t+1}\phi(\omega_{t+1}|s_{t+1})d\omega_{t+1} + \bar{\omega}_{t+1}\left[1-\Phi(\bar{\omega}_{t+1}, s_{t+1})\right]. \quad (42)$$

By the law of large numbers, equation (42) can be interpreted as the fraction of the expected capital returns that accrues to the average lender.

As explained in the appendix, the formal contracting problem reduces to choosing the quantity of physical capital, K_{t+1}, and the threshold, ω_{t+1}, that maximize the entrepreneurs' expected nominal return on capital net of the loan costs (see equation 39):

$$P_t Q_t K_{t+1} E_t(R^e_{t+1})\left[1 - J(s_{t+1}) - \Gamma(\bar{\omega}_{t+1}, s_{t+1})\right], \quad (43)$$

subject to the participation constraint for lenders (see equation 41), that is,

$$\begin{aligned} &P_t Q_t K_{t+1} E_t(R^e_{t+1})\Gamma(\bar{\omega}_{t+1}, s_{t+1}) - \mu G(\bar{\omega}_{t+1}, s_{t+1}) \geq I^b_{t+1} L_{t+1} \\ &= I^b_{t+1}(P_t Q_t K_{t+1} - N_{t+1}). \end{aligned} \quad (44)$$

We write the share of capital returns going to the entrepreneurs as

$$f(\bar{\omega}_{t+1}, s_{t+1}) = 1 - J(s_{t+1}) - \Gamma(\bar{\omega}_{t+1}, s_{t+1}) \quad (45)$$

and the share going to the lender as

$$g(\bar{\omega}_{t+1}, s_{t+1}) = \Gamma(\bar{\omega}_{t+1}, s_{t+1}) - \mu\ \mathrm{G}(\bar{\omega}_{t+1}, s_{t+1}). \quad (46)$$

For more details on the characterization of the functions $\Gamma(\bar{\omega}_{t+1}, s_{t+1})$ and $G(\bar{\omega}_{t+1}, s_{t+1})$, see the appendix.

Solving this optimization problem results in two additional equilibrium conditions. On the one hand, the participation constraint for the lenders becomes

$$\frac{P_t Q_t K_{t+1}}{N_{t+1}} = \frac{1}{1 - \left\{\dfrac{\Psi(\bar{\omega}_{t+1}, s_{t+1}) + \Gamma(\bar{\omega}_{t+1}, s_{t+1}) - \left[1 - J(s_{t+1})\right]}{\Psi(\bar{\omega}_{t+1}, s_{t+1})}\right\}}, \quad (47)$$

which implies that the threshold $\bar{\omega}_{t+1}$ can be viewed as a function of variables that are either known or observed at time t, that is,

$$\bar{\omega}_{t+1} \equiv \bar{\omega}\left(\frac{P_t Q_t K_{t+1}}{N_{t+1}}, s_{t+1}\right).$$

The expression $\Psi(\bar{\omega}_{t+1}, s_{t+1})$ is defined in the appendix as

$$\begin{aligned}\Psi(\bar{\omega}_{t+1}, s_{t+1}) \equiv\, & 1 - J(s_{t+1}) - \Gamma(\bar{\omega}_{t+1}, s_{t+1}) \\ & + \lambda(\bar{\omega}_{t+1}, s_{t+1})\left[\Gamma(\bar{\omega}_{t+1}, s_{t+1}) - \mu G(\bar{\omega}_{t+1}, s_{t+1})\right],\end{aligned} \tag{48}$$

where $\lambda(\bar{\omega}_{t+1}, s_{t+1})$ is the Lagrange multiplier on the lenders' participation constraint in equation (44) (and represents the shadow cost of enticing the participation of the lenders). The threshold depends not only on the anticipated systemic risk shock, s_{t+1}, but also on the asset-to-net-worth ratio of the entrepreneur-borrower, $P_t Q_t K_{t+1}/N_{t+1}$. Given the relationship in equation (32), the asset-to-net-worth ratio can be related to the leverage borrower as

$$\frac{P_t Q_t K_{t+1}}{N_{t+1}} = 1 + \frac{L_{t+1}}{N_{t+1}}, \tag{49}$$

where L_{t+1}/N_{t+1} is a conventional measure of the debt-to-net-worth ratio of the entrepreneur. Moreover, it can be argued that a formulation for the external financing premium arises in the following terms:

$$E_t(R^e_{t+1}) = s\left(\frac{P_t Q_t K_{t+1}}{N_{t+1}}, s_{t+1}\right) I^b_{t+1}. \tag{50}$$

This characterization of the external financing premium expands the Bernanke-Gertler-Gilchrist framework by adding the explicit possibility that the spread itself be affected by the impact of an anticipated aggregate shock, s_{t+1}. However, we preserve the key feature of the financial accelerator model, which is the linkage between the spread on capital returns and the leverage of the entrepreneurs-borrowers. Moreover, the costly state verification theory implies that external funding (loans) is more expensive than internal funding (the entrepreneurs' savings).

1.5.3 The optimal capital investment for the entrepreneurs

As noted earlier, the entrepreneurs obtain income from managerial labor at a competitive nominal wage, W_t^e, and from renting capital to wholesale firms and reselling the depreciated capital to the capital goods producers, $\omega_{t+1}R_{t+1}^e P_t Q_t K_{t+1}$. With these resources at hand, each entrepreneur must repay the previous period loans at the agreed rate (that is, they must repay $I_t^l L_t = \overline{\omega}_{t+1} R_{t+1}^e P_t Q_t K_{t+1}$) or choose to default. The entrepreneur must also finance his own consumption, C_t^e, acquire new capital from the capital producers, $P_t Q_t K_{t+1}$, and repay L_{t+1}. In this environment, the budget constraint of a representative entrepreneur can be described in the following terms:

$$P_t C_t^e + P_t Q_t K_{t+1} \leq W_t^e H_t^e + \left[1 - J(s_t) - \Gamma(\overline{\omega}_t, s_t)\right] R_t^e P_{t-1} Q_{t-1} K_t - P_t C_t^e. \quad (51)$$

Using the equilibrium participation constraint as expressed in equation (47) to replace $P_{t-1}Q_{t-1}K_t$, it immediately follows that

$$N_{t+1} \leq W_t^e H_t^e + \Psi(\overline{\omega}_t, s_t) R_t^e N_t - P_t C_t^e. \quad (52)$$

Based on this characterization of the budget constraint of the representative entrepreneur, we can infer that an interior solution of his optimization problem in which equation (52) holds with equality can be obtained as the solution to an equivalent maximization problem, according to which the entrepreneur chooses his real net worth, N_{t+1}/P_t, to maximize

$$\sum_{\tau=0}^{+\infty} (\beta\eta)^\tau E_t \left[\frac{W_{t+\tau}^e}{P_{t+\tau}} + \Psi(\overline{\omega}_{t+\tau}, s_{t+\tau}) R_{t+\tau}^e \frac{P_{t+\tau-1}}{P_{t+\tau}} \frac{N_{t+\tau}}{P_{t+\tau-1}} - \frac{N_{t+\tau+1}}{P_{t+\tau}} \right], \quad (53)$$

where we implicitly use the fact that managerial labor is inelastically supplied and normalized to one (as pointed out in equation 31).

This intertemporal optimization must satisfy the following Euler equation:

$$1 = \beta\eta E_t \left[\Psi(\overline{\omega}_{t+1}, s_{t+1}) R_{t+1}^e \frac{P_t}{P_{t+1}} \right], \quad (54)$$

which determines the consumption-savings margin for the representative entrepreneur. The left-hand side of equation (54) is

the marginal utility of entrepreneurs' consumption. The right-hand side is the expected discounted real rate of return of acquiring a unit of capital after taking into account the costs associated with the need for external funding. The latter term has two components. The first term, $\Psi(\bar{\omega}_{t+1}, s_{t+1})$, captures the effect of default on external borrowing costs and also accounts for the role of anticipated systemic losses. The second component, $R^e_{t+1}(P_t / P_{t+1})$, is the real rate of return on capital whenever the resale value of depreciated capital and the acquisition cost of new capital are equalized.

1.6 Banks

There is a continuum of banks of unit mass. All banks are systemic and perfectly competitive, so they take all prices as given. The bank offers the households two types of assets for investment purposes: one that we call bank equity and another that we call one-period deposits. Deposits offer a nominal risk-free rate, while equity is rewarded with a riskless return in every period that induces households-shareholders to hold bank capital as well. All households who own bank equity must be indifferent between investing in equity or simply making a deposit.

For convenience, we define the safe return promised to the equity holders in terms of a yield, R^e_{t+1}, over the value of the banks equity, B_{t+1}. Household deposits are perfectly insured and pay a risk-free rate, I_{t+1}. Banks use all the resources they attract (deposits and bank capital) to offer one-period loans to the entrepreneurs with the conditions described above. At the end of each loan contract, all unanticipated profits accrued by the bank are rebated (lump-sum) to the households independently of their portfolio allocation between the bank's liabilities (deposits) and equity.

At the end of period t, the balance sheet of the banking system can be summarized as follows:

$$L_{t+1} + \varpi D_{t+1} = B_{t+1} + D_{t+1}, \tag{55}$$

where the right-hand side describes the liabilities (that is, the deposits) taken at time t, D_{t+1}, and the equity offered at the same time, B_{t+1}. The left-hand side shows the assets, $L_{t+1} + \varpi D_{t+1}$. Among the assets, we count the reserves on deposits maintained at the central bank (that is, ϖD_{t+1}, where $0 \leq \varpi \leq 1$ represents the compulsory reserve requirement on nominal deposits set by the regulator) and

the loans offered at time t, L_{t+1}. As a matter of convention, D_{t+1} denotes nominal deposits and L_{t+1} nominal loans held from time t to $t+1$. Similarly, B_{t+1} is the bank capital outstanding between time t and time $t+1$.

We can rewrite the balance sheet more conveniently as

$$L_{t+1} = \left(\frac{1-\varpi}{1-\upsilon_{t+1}}\right) D_{t+1}, \tag{56}$$

where we define the leverage ratio on bank capital as $\upsilon_{t+1} \equiv (B_{t+1}/L_{t+1})$. In other words, the rate at which deposits are transformed into loans is affected by the compulsory reserve requirement and by the bank's capital leverage policy. In Bernanke, Gertler, and Gilchrist (1999), with $\varpi = 0$ and no bank equity (that is, $\upsilon_{t+1} = 0$), the transformation rate is one to one. It thus holds that $L_{t+1} = D_{t+1}$. Although the model preserves the basic underlying structure of the bank's balance sheet in Bernanke, Gertler, and Gilchrist (1999), equation (56) indicates that the regulatory features should play a significant role on the cost structure of loan supply.

The banks' profits on a given one-period loan contract are realized at time $t+1$. We can express the profits of the banking system as

$$\begin{aligned} \Pi^b_{t+1} \equiv\ & R^e_{t+1} P_t Q_t K_{t+1} \left[\Gamma(\bar{\omega}_{t+1}, s_{t+1}) - \mu G(\bar{\omega}_{t+1}, s_{t+1})\right] \\ & + \varpi \bar{I}_{t+1} D_{t+1} - R^b_{t+1} B_{t+1} - I_{t+1} D_{t+1}, \end{aligned} \tag{57}$$

while the expected profits at the time the loan is contracted should be

$$E_t\left(\Pi^b_{t+1}\right) \equiv I^b_{t+1} L_{t+1} + \varpi \bar{I}_{t+1} D_{t+1} - R^b_{t+1} B_{t+1} - I_{t+1} D_{t+1}. \tag{58}$$

The required nominal participation returns on loans, I^b_{t+1}, are determined at time t when the loans are signed between the banks-lenders and the entrepreneurs-borrowers (see the participation constraint in equation 44). Deposits held at the central bank in the form of reserves are also returned to the banks. We assume that they earn an interest on reserves, $\bar{I}_{t+1}$, which is known at time t and designed as a two-part rate:

$$\bar{I}_{t+1} \equiv (1-c) + \zeta(I_{t+1} - 1), \tag{59}$$

whereby banks pay a fixed fee as a management cost per unit of reserve held at the central bank, and $0 < \zeta < 1$ denotes the discount rate relative to the monetary net short-term rate at which reserves are compensated. Although in most instances the practice is to set this rate of return to zero (that is, $c = \zeta = 0$), there are precedents for paying interest on reserves.[7] We also make the simplifying assumption that there is full deposit insurance, so that deposits are riskless and the gross interest rate paid on deposits is equal to the risk-free nominal rate, I_{t+1}, which is known at time t.

Bank capital shareholders (that is, the households) have to be compensated with a certain nominal yield, R^b_{t+1}, determined at time t. Since at time t expected profits depend exclusively on variables that are chosen and known at that time by the banks and the households, competitive banks must end up offering a yield to the shareholders that is also known at time t. By arbitrage implied in equations (3) and (4), it must therefore be the case that

$$(1-\iota^h)R^b_{t+1} = I_{t+1}, \tag{60}$$

which ensures that households remain indifferent between holding bank capital or deposits. For a competitive banking sector, the expected profit function in equation (58) must satisfy a zero-expected profit condition (that is, $\Pi^b_{t+1} = 0$) in the following terms:

$$E_t\left(\Pi^b_{t+1}\right) \equiv \left[I^b_{t+1} - \upsilon_{t+1}R^b_{t+1} - (1-\upsilon_{t+1})\left(\frac{I_{t+1} - \varpi\bar{I}_{t+1}}{1-\varpi}\right)\right]L_{t+1} = 0. \tag{61}$$

After using the balance sheet equation in equation (56). The banks' problem is to optimize their capital structure to reflect the trade-off between bank equity and deposits, subject to the constraint that banks must offer a yield on bank capital that makes households indifferent given the existing option of a risk-free rate on deposits as given by equation (60). Of course, this problem is also subject to the feature of the central bank's policy of paying reserves as given

7. Until very recently, reserve requirements held at the Federal Reserve did not earn interest. The Federal Reserve announced changes to reserve management after winning the power to pay interest on required and excess reserves on 3 October 2008. The Federal Reserve has argued that paying interest would deter banks from lending out excess reserves and as such would make it easier for the Fed to attain its target rate. We do not attempt to model this feature explicitly.

by equation (61) and subject to a regulatory constraint on capital adequacy that implies banks must satisfy

$$1 \geq \upsilon_{t+1} \equiv \frac{B_{t+1}}{L_{t+1}} \geq \upsilon, \tag{62}$$

where $0 \leq \upsilon < 1$ is equal to the minimum mandatory capital adequacy requirement set by the regulator.[8] The lower bound, υ, may also reflect a buffer above the minimum regulatory requirement implied by the statutory requirements of the banks themselves, and it could even be time-varying over the cycle.

We make two key parametric assumptions to simplify the problem of the banks, and we leave the exploration of more complex banking cost structures for future research. Our goal at this stage is to make only the smallest possible departure from the original Bernanke-Gertler-Gilchrist framework. We assume that $\zeta = 1 - c$ and that taxes on bank equity are bounded by $0 < 1 - \iota^h < (1 - \varpi) / (1 - \zeta\varpi)$. Whenever $\xi = 0$, this bound implies that $\iota^h > \varpi$; whenever $\xi = 1$, it merely requires that $\iota^h > 0$. Given the fact that tax rates are quite often much higher than the minimum reserve ratios, these bounds are not excessively restrictive.

The two assumptions together imply that

$$R^b_{t+1} > \left(\frac{I_{t+1} - \varpi \bar{I}_{t+1}}{1 - \varpi} \right). \tag{63}$$

In other words, it is costlier for banks to finance themselves with bank equity than with deposits. Therefore, the lower bound on the leverage ratio must be binding at all times.

8. The current regulatory regime was shaped primarily by the 1988 international Basel Accord and the 1991 Federal Deposit Insurance Corporation Improvement Act (FDICIA). The Basel Accord established minimum capital requirements as ratios of two aggregates of accounting capital to risk-weighted assets (and certain off-balance-sheet activities). The risk weights are supposed to reflect credit risk. For example, commercial and industrial loans have a weight of one, while U.S. government bonds have zero weight and consequently do not require any regulatory capital. Primary or tier 1 (core) capital (equal to the book value of the bank's stock plus retained earnings) is required to exceed 4 percent of risk weighted assets, while total (tier 1 plus tier 2) capital must be at least 8 percent. In calculating the risk-weighted capital asset ratio, all loans are assumed to be in the highest risk category in the sense of the Basel Accord, with a risk weight of 100 percent. This category includes all claims to the nonbank private sector, except for mortgages on residential property, which receive a risk weight of 50 percent. The riskless securities are in the lowest risk category, with a weight of zero. Typical examples are Treasury bills and short loans to other depository institutions.

These assumptions imply that the participation rate of return required by the banks to fund the entrepreneurs is fully determined by the cost structure of the banks themselves, as follows:

$$\begin{aligned} I^b_{t+1} &= \upsilon R^b_{t+1} + (1-\upsilon)\left(\frac{I_{t+1} - \varpi \bar{I}_{t+1}}{1-\varpi}\right) \\ &= \left[\upsilon\left(\frac{1}{1-\iota^h}\right) + (1-\upsilon)\left(\frac{1-\varpi\zeta}{1-\varpi}\right)\right] I_{t+1}. \end{aligned} \tag{64}$$

This is what we call the balance sheet channel of banking regulation. Without capital adequacy requirements (that is, $\upsilon = 0$) and without reserve requirements (that is, $\varpi = 0$), we would be back to the world of Bernanke, Gertler, and Gilchrist (1999), where $I^b_{t+1} = I_{t+1}$. Our equation (64) is a heavily parametrized version of the following expression for returns on the portfolio of loans under constant returns to scale:

$$\frac{I^b_{t+1}}{I_{t+1}} \equiv \upsilon_{t+1} \times \frac{\text{cost}(bank\,equity_{t+1})}{I_{t+1}} + (1-\upsilon_{t+1}) \times \frac{\text{cost}(deposits_{t+1})}{I_{t+1}}, \tag{65}$$

where υ_{t+1} represents the leverage ratio as before. The realized profits at the time the loan contract expires in equations (57) can, alternatively, be represented as

$$\Pi^b_{t+1} \equiv \left[R^b_{t+1} - E_t(R^b_{t+1})\right] P_t Q_t K_{t+1} \left[\Gamma(\bar{\omega}_{t+1}, s_{t+1}) - \mu G(\bar{\omega}_{t+1}, s_{t+1})\right], \tag{66}$$

where we have used the participation constraint in equation (44) appropriately. Hence, the realized profits reflect the intertemporal aggregate risks associated with the portfolio of loans supplied to the entrepreneurs (which is captured by the margin $R^e_{t+1} - E_t(R^e_{t+1})$) on the asset side of the banks' balance sheet. The assumption that all realized profits are rebated to the households (no profits are retained by the banks) transfers the consequences of the aggregate risks to the households, who cannot avoid them by adjusting their portfolio between bank equity and bank deposits. We leave for future research the exploration of a more complex environment in which banks' dividends are related to equity holdings and, more interestingly, in which retained profits can affect the evolution of bank equity and expose bank capital to aggregate risks.

1.7 Government

We close our description of the model with the specification of a consolidated (and balanced) budget constraint and an interest rate rule for monetary policy. We assume that government expenditures and the subsidy on inputs for retailers are financed through lump-sum taxes on households, taxes on bank equity, and seigniorage, that is,

$$\begin{aligned} P_t G_t + T_t + \iota^h R_t^b B_t + M_{t+1} &= \iota^r P_t^w \left[\int_0^1 Y_t(z) dz \right] + \bar{I}_t M_t \\ &= \iota^r P_t^w Y_t^w + \bar{I}_t M_t, \end{aligned} \tag{67}$$

where G_t denotes real government expenditure. We assume for simplicity that government consumption is equal to zero in every period, that is, $G_t = 0$. The characteristics and bounds on the tax subsidy for retailers, ι^r, and the tax rate on dividends, ι^h, as well as the nature of the nondistortionary (lump-sum) tax or transfer to the households, T_t, have already been discussed elsewhere. The government also funds its operations by issuing high-powered money (the monetary base), M_{t+1}, at time t.

For the purpose of defining the monetary base, money consists only of the total reserves of the banking sector on their accounts at the central bank. Therefore, given the compulsory requirement on reserves, the equilibrium in the money market requires that

$$M_{t+1} = \varpi D_{t+1}. \tag{68}$$

As noted before, reserves deposited at time t accrue a rate of return $\bar{I}_t$, which is characterized by the formula in equation (61). For simplicity, money plays exclusively the role of a unit of account and acts as the counterpart for deposit reserves on the balance sheet of the central bank.

The central bank policy is modeled by means of an interest rate reaction function. In the spirit of Taylor (1993), the policy rule targets the short-term nominal interest rate, I_{t+1}, and is linear in the logs of the relevant arguments:

$$i_{t+1} = \rho_i i_t + (1-\rho_i) \left[\psi_\pi \ln\left(\frac{P_t}{P_{t+1}} \right) + \psi_q \ln(Q_t) + \psi_y \ln(Y_t) \right] + m_t, \tag{69}$$

where $i_t \equiv \ln(I_t)$ is the logarithm of the risk-free rate. In line with most of the literature, we assume that the monetary authority is willing to smooth changes in the actual short-term nominal interest rate, that is, $0 \leq \rho_i \leq 1$, where ρ_i is the smoothing parameter. The other parameters in the reaction function satisfy $\psi_\pi \geq 1$, $-\infty < \psi_1 < +\infty$, and $\psi_y \geq 0$. The monetary shock in logs, m_t, follows an AR(1) process of the following form:

$$m_t = \rho_m m_{t-1} + \varepsilon_t^m, \tag{70}$$

where ε_t^m is a zero mean, uncorrelated, and normally distributed innovation. The parameter $-1 < \rho_m < 1$ determines the persistence of the monetary shock and $\sigma_m^2 > 0$ the volatility of its innovation.

A few observations on the specification of equation (69) are in order. First, we model monetary policy in terms of an implementable rule, whereby the central bank sets the short-term nominal interest rate in response to observable variables only. Second, this general specification allows the monetary policy instrument to react to deviations of the relative price of capital goods, Q_t, from its long-run value of one. This is the channel through which we allow asset price fluctuations to feed into the setting of monetary policy.

Third, equation (71) can always be rewritten in terms of a pure trade-off between inflation and output, as follows:

$$\begin{aligned} i_{t+1} = & \left\{ \rho_i + \psi_q (1-\rho_i) \left[\frac{\ln(Q_t)}{i_t - \ln\left(\frac{P_t}{P_{t-1}}\right)} \right] \right\} i_t \\ & + (1-\rho_i) \left\{ \left[\psi_\pi - \psi_q \frac{\ln(Q_t)}{i_t - \ln\left(\frac{P_t}{P_{t-1}}\right)} \right] \ln\left(\frac{P_t}{P_{t-1}}\right) + \psi_y \ln(Y_t) \right\} + m_t, \end{aligned} \tag{71}$$

where the coefficient on inflation and the inertia parameter vary depending on whether Tobin's Q is growing faster than the ex post real interest rate. This is obviously one of many observationally equivalent rules that we could write that are consistent with the structure of equation (69). In more general terms, it would be rather

appealing to fix monetary policy in terms of a well-known trade-off between inflation and output, but at the same time allow flexibility for the rule to respond differently to systemic risk, which is a critical source of uncertainty in our framework.

The specification of the Taylor rule that we have in mind would take the following form:

$$\begin{aligned} i_{t+1} &= \rho_i(s_t - \bar{s})i_t \\ &+ \left[1 - \rho_i(s_t - \bar{s})\right]\left[\psi_\pi(s_t - \bar{s})\ln\left(\frac{P_t}{P_{t-1}}\right) + \psi_y(s_t - \bar{s})\ln(Y_t)\right] + m_t, \end{aligned} \tag{72}$$

where the inertia and the weights on inflation and output are a function of the perceived riskiness of the current environment as determined by the distance of the actual systemic risk shock realization, s_t, relative to the breaking point after which losses in the secondary market for used capital become catastrophic.

1.7.1 Resource constraint

Equilibrium in the final goods market requires that the production of the final good be allocated to total private consumption by households and entrepreneurs (and possibly the government), to investment by capital goods producers, and to covering the costs that originate from the monitoring technology required to enforce the loan contract described earlier (and in the appendix). That is,

$$Y_t = C_t + C^e + G_t + X_t + \underbrace{\mu G(\bar{\omega}, s_t) R_t^e \frac{P_{t-1}}{P_t} Q_{t-1} K_t}_{\text{Loss from monitoring costs}}, \tag{73}$$

where final output and wholesale output are related as $Y_t = (P_t^* / P_t)^\theta Y_t^w$. In the above equation, the impact of government consumption is trivial since we have assumed for simplicity that G_t=0. In the Bernanke-Gertler-Gilchrist model, government consumption evolves exogenously and is assumed to be financed through lump-sum taxes. A similar extension can be implemented in our setting.

2. Discussion and Interpretation

The relationship in equation (64) clearly ties the participation return, I^b_{t+1}, to the risk-free rate, I_{t+1}, which happens to also be the relevant instrument for monetary policy. The regulatory restriction on capital adequacy in equation (62) does not prevent bad outcomes from happening. Instead, the purpose of this regulatory constraint is to effectively give the monetary authority a way to regulate the supply of loans without having to manipulate the interest rate directly. In that sense, we can visualize the banks' balance sheet channel in this framework by combining equations (50) and (64) as follows:

$$E_t(R^e_{t+1}) = \underbrace{s\left(\frac{P_t Q_t K_{t+1}}{N_{t+1}}, s_{t+1}\right)}_{\text{Agency costs channel, as in BGG (1999)}} \underbrace{\left[\upsilon\left(\frac{1}{1-\iota^h}\right) + (1-\upsilon)\left(\frac{1-\varpi\zeta}{1-\varpi}\right)\right]}_{\text{Balance sheet channel} \geq 1} I_{t+1}. \quad (74)$$

This equation shows that the balance sheet channel has the potential to amplify the external financing premium spread. However, because this channel is regulated by the central bank, the monetary authority can potentially manipulate the requirements to reduce the amplification effect when the agency cost component is rising.

We have a fairly standard setting that quite closely follows the derivation of the equilibrium conditions in Bernanke, Gertler, and Gilchrist (1999), so our linearization shows obvious similarities with theirs. The main differences arise because we have introduced frictions in the secondary market for used capital that have the potential to alter the conditions under which borrowers and lenders operate in this economy, and because we have expanded the balance sheet of the banks-lenders to give banking regulation a role in loan pricing decisions.

Entrepreneurs cannot borrow at the riskless rate as revealed in equation (74). The cost of external financing differs from the risk-free rate because the idiosyncratic component to their returns on capital is unobservable from the banks' point of view. To infer the realized return of the entrepreneur, the bank has to pay a monitoring cost. The banks monitor the entrepreneurs that default, pay the verification cost, and seize the remaining capital income. In equilibrium, entrepreneurs borrow up to the point at which the expected return on capital equals the cost of external financing:

$$E_t(\hat{r}^e_{t+1}) \approx \hat{i}_{t+1} + \vartheta\,(\hat{p}_t + \hat{q}_t + \hat{k}_{t+1} - \hat{n}_{t+1}) + \Lambda\hat{\upsilon}_{t+1} + \Theta\hat{s}_{t+1}, \quad (75)$$

where $\hat{k}_{t+1}$ denotes capital, $\hat{n}_{t+1}$ is the entrepreneur's net worth, $\hat{q}_t$ is Tobin's Q, $\hat{p}_t$ is the CPI, $\hat{i}_{t+1}$ is the risk-free rate, $\hat{\upsilon}_{t+1}$ determines changes in banking regulation (capital adequacy) or the bank's leverage policy, and $\hat{s}_{t+1}$ stands for the systemic risk shock that capture the distortions in the secondary market for used capital. The composite parameters ϑ, Λ, and Θ can be expressed as a function of the structural parameters of the model, and all variables in lowercase letters with an over hat represent log deviations from the steady state.

The right-hand side of the external financing premium equation in equation (75) can be decomposed into two terms: the nominal risk-free rate and the external financing premium.[9] The parameter ϑ measures the elasticity of the external financing premium to variations in leverage of the entrepreneurs, measured by their capital expenditures relative to net worth. The larger the share of the capital purchase financed with the entrepreneurs' net worth, the closer the spread is to zero and the lower the associated moral hazard. If entrepreneurs have sufficient savings to finance the entire capital stock, then agency problems vanish, and the risk-free rate and the expected return to capital income must coincide unless either the banks' leverage, $\hat{\upsilon}_{t+1}$, or systemic risk $\hat{s}_{t+1}$, vary. So far, this is the same result found in Bernanke, Gertler, and Gilchrist (1999). Our model, however, illustrates that changes in banking regulation on capital adequacy and systemic risk add a new dimension to the external financing premium that cannot be discounted.

Two points warrant further discussion here. First, our specification of a Taylor rule in equation (72) depends on exogenous shocks that are potentially unobservable to policymakers. Second, our characterization of banks, while more complete than Bernanke, Gertler, and Gilchrist (1999), is nonetheless simple. The remainder of this section addresses these issues.

2.1 Taylor Rules

A potential disadvantage of our specification of the Taylor rule in equation (72), namely,

9. The key mechanism involves the link between the external financing premium (that is, the difference between the cost of funds raised externally and the opportunity cost of internal funds) and the net worth of the entrepreneurs-borrowers.

$$i_{t+1} = \rho_i(s_t - \bar{s})i_t + \left[1 - \rho_i(s_t - \bar{s})\right]\left[\psi_\pi(s_t - \bar{s})\ln\left(\frac{P_t}{P_{t-1}}\right) + \psi_y(s_t - \bar{s})\ln(Y_t)\right] + m_t, \tag{76}$$

is that monetary policy depends on an exogenous shock that is not necessarily observable to the policymaker, the systemic shock s_t. An alternative is to explore a policy rule reflecting the assumption that monetary authorities readjust the weights on inflation and output in response to the other observable variables every period, reacting to asset prices, Q_t, as in out conjecture in equation (69). That is,

$$i_{t+1} = \rho_i(s_t - \bar{s})i_t + (1 - \rho_i)\left[\psi_\pi \ln\left(\frac{P_t}{P_{t-1}}\right) + \psi_q \ln(Q_t) + \psi_y \ln(Y_t)\right] + m_t. \tag{77}$$

We could even explore alternative rules in which the central bank's response depends on the size of the spreads between the risk-free rate and the implied returns on capital, along the lines of Curdia and Woodford (2008). A potential specification that fits our environment is

$$i_{t+1} = \rho_i(s_t - \bar{s})i_t + (1 - \rho_i)\left[\psi_\pi \ln\left(\frac{P_t}{P_{t-1}}\right) + \psi_a \ln\left(\frac{P_t Q_t K_{t+1}}{N_{t+1}}\right) + \psi_y \ln(Y_t)\right] + m_t. \tag{78}$$

This rule targets the leverage ratio of the borrowers, since theory tells us that this is the unobservable component of the external financial premium in equation (74).

As noted above, specification (77) is comparable to the Taylor rule presented in equation (76), and they produce similar results when implemented as long as Tobin's Q is a sufficient statistic for the unobservable systemic shock. The same can be said of the specification in equation (78). Whether such Taylor rules are optimal relative to a rule with constant coefficients will likely depend on whether the observable variables (Tobin's Q or the spreads) are good proxies for signaling trouble in the secondary market for used capital. Monetary policy is likely to improve its performance if it can react to strong signals, but it probably will not do better than under an old-fashioned Taylor rule with constant coefficients if the signal

is weak or gives the wrong message depending on the nature of the shock that hits the economy.

The transmission mechanism that affects the dynamics of the economy over the business cycle is also quite important here. Monetary policy has no direct effect on the systemic shock in equation (75), since this shock is assumed to be exogenous. However, the central bank can either alter the bank regulatory requirements, $\hat{\upsilon}_{t+1}$, or the short-term interest rate, $\hat{i}_{t+1}$, to offset fluctuations of the spread that tend to increase the volatility of the cost of external borrowing for the entrepreneurs and potentially lead to periods of excessive investment or underinvestment. Monetary policy, whether implemented conventionally through interest rate movements or by changes in banking regulation, would nonetheless have an indirect effect on the equilibrium spreads, which can limit the effectiveness of those actions.

2.2 Banking Sector

Arguably, our model remains a very naïve characterization of the behavior of banks. We are far from having an integrated model of the business cycle in which banks operate in multiple periods, with a portfolio of loans of different maturities, and simultaneously confront friction in their lending operations and nontrivial distortions in the way they raise capital or attract depositors. However, this characterization of the economy emphasizes the regulatory power to alter the operational costs of the banking system. Even in this simplified framework, it immediately transpires that the regulator is able to alter the terms of the banks' operating costs. The regulator thus has at hand a tool to either amplify or reduce the loan supply without directly changing the short-term interest rate. This framework offers a way to explore how the model responds to monetary policy and regulatory features.

We have already noted that regulatory features can be modified with the intention of offsetting fluctuations in the spread faced by borrowers on external funding. In principle, given the fact that reserve requirements and capital adequacy requirements are not excessively punitive in most developed countries, one might expect that changes in banking regulation would have small effects on the cost structure of banks and, therefore, would have less of an impact on the cost of borrowing for entrepreneurs. However, in the extreme case in which $\hat{\upsilon}_{t+1} = -(\Theta/\Lambda)\hat{s}_{t+1}$, it might be possible to entirely eliminate

the effect of systemic risk on shocks without altering the interest rate. It might therefore be possible to limit the impact of the systemic risk shock on the economy without having to alter the entrepreneurs' incentives to invest and the households' incentives to save.

While the potential for banking regulation to play a countercyclical role is present in the model, and noted in our comments, it is not easy to obtain a clear signal of the risks confronted. In most instances, the systemic risks, $\hat{s}_{t+1}$, are simply not observable, and relying on observables to define the cyclical patterns of banking regulation is as difficult as it was for setting the interest rate rule. In practice, however, the banking leverage ratios tend to be procyclical and contribute to amplifying the cycle, so the policy debate is more oriented toward policies that would reduce those tendencies than turning banking regulation into a cyclical counterbalance.

3. Concluding Remarks

Our paper has set forth a model of the economy that generalizes the Bernanke-Gertler-Gilchrist model to include a compact characterization of both the financial accelerator and the role of the financial sector in propagating monetary policy to the real economy. We have identified the output costs of systemic risk and the agency costs of costly state verification, as well as their role in determining the external finance premium. Equation (74) neatly summarizes this relationship and makes clear how the financial sector can amplify the cycle as discussed in Bernanke, Gertler, and Gilchrist (1999). This characterization provides a parsimonious explanation that can be compared with existing research on the interaction between monetary policy and bank regulation. This result arises as part and parcel of a model designed to explain the transmission and amplification of monetary action.

A model that includes this type of lending channel can go some length toward explaining the monetary policy asymmetries that Taylor rules have been unable to account for in the last few years. Moreover, since our model is built around the existence of a regulatory capital constraint, it provides the basis for discussing the implication of joint determination of monetary policy and regulation. Indeed, the presence of differences in monetary policy discussed in this model implies a strong incentive for the joint monetary/regulatory authority to ensure that financial institutions remain above the capital constraint. In times of falling asset values, banks will approach or fall

below capital requirements, rendering monetary policy ineffective at stimulating lending. At this point, the monetary/regulatory authority has a stronger incentive to lower capital requirements in order to facilitate monetary intervention. If falling asset values were due to a realization of inaccurate risk measurements, reduced capital levels may simply encourage reckless lending.

With this framework in place, there are potentially more open questions ahead (and, unfortunately, beyond the scope of this paper). For example, while the model appears to do a reasonably good job of describing the stylized patterns of the U.S. monetary authority during the recent crisis (at least in suggesting that the reduction of interest rates are a plausible policy response to systemic shocks and bank lending constraints), it is nonetheless potentially rejected by the European case. The European Central Bank held interest rates constant until late 2008. Though there are many possible reasons for this, we speculate that it emerges, in part, from differences in mandate. The Federal Reserve has responsibility for both monetary policy and bank regulation. This produces well-known conflicts between the goals of monetary policy and bank regulation. It also produces an incentive to keep banks above regulatory thresholds through the use of monetary policy (see Cecchetti and Li, 2008, on neutralization of the capital constraint).

Appendix
The Loan Contract

With regard to the aggregate sharing of capital income, we define the following two variables for simplicity of notation,

$$\Gamma(\bar{\omega}_{t+1}, s_{t+1}) \equiv \int_0^{\bar{\omega}_{t+1}} \omega_{t+1}\phi(\omega_{t+1}|s_{t+1})d\omega_{t+1} + \bar{\omega}_{t+1}\left[1-\phi(\bar{\omega}_{t+1}, s_{t+1})\right]; \tag{A1}$$

$$\mu G(\bar{\omega}_{t+1}, s_{t+1}) \equiv \mu \int_0^{\bar{\omega}_{t+1}} \omega_{t+1}\phi(\omega_{t+1}|s_{t+1})d\omega_{t+1}. \tag{A2}$$

Then, we can rewrite the share of capital returns going to the lenders in equation (42) more compactly as

$$g(\bar{\omega}_{t+1}, s_{t+1}) = \Gamma(\bar{\omega}_{t+1}, s_{t+1}) - \mu G(\bar{\omega}_{t+1}, s_{t+1}). \tag{A3}$$

Given the definition of the capital returns share going to entrepreneurs in equation (40), it also follows that

$$\begin{aligned} f(\bar{\omega}_{t+1}, s_{t+1}) &= \int_0^{+\infty} \omega_{t+1}\phi(\omega_{t+1}, s_{t+1})d\omega_{t+1} - \Gamma(\bar{\omega}_{t+1}, s_{t+1}) \\ &= 1 - J(s_{t+1}) - \Gamma(\bar{\omega}_{t+1}, s_{t+1}), \end{aligned} \tag{A4}$$

where the second equality follows from our characterization of the expectation of the idiosyncratic shock in equation (36). Based on these definitions, we can infer that the capital income sharing rule resulting from this financial contract satisfies

$$f(\bar{\omega}_{t+1}, s_{t+1}) + g(\bar{\omega}_{t+1}, s_{t+1}) = 1 - J(s_{t+1}) - \mu G(\bar{\omega}_{t+1}, s_{t+1}), \tag{A5}$$

where $J(s_{t+1}) \equiv 1 - E_t(\omega_{t+1} \mid s_{t+1})$ accounts for the expected systemic losses on the resale value of capital and $\mu G(\bar{\omega}_{t+1}, s_{t+1})$ characterizes the conventional monitoring costs and probability of default associated with the costly-state verification framework.

The functions $f(\bar{\omega}_t, s_t)$ and $g(\bar{\omega}_t, s_t)$ represent the sharing rule between entrepreneurs-borrowers and banks-lenders on the capital returns required by the entrepreneur's partial use of one-period external loans to fund its risky capital investment. Both of them depend on the realization of the systemic risk shock, s_{t+1}. However, as can be inferred from equation (A5), they do not add up to one.

A fraction of the capital income, $J(s_{t+1})$, is transferred to the capital goods producers as a result of inefficiencies in the secondary market for used capital, while another fraction, $\mu G(\bar{\omega}_{t+1}, s_{t+1})$, is lost due to the burden of monitoring. Only monitoring costs result in a direct loss of capital income that detracts resources, as shown in the resource constraint in equation (75), but the fact that resources are siphoned out of the hands of borrowers and lenders due to market imperfections somewhere else still has the potential to substantially distort the incentives of both parties involved in the loan contract and, therefore, to affect the funding of investment in new capital.

The optimization problem

We conjecture that the threshold, $\bar{\omega}_{t+1}$, would be defined as a function of the systemic risk shock, s_{t+1}, and the assets-to-net-worth ratio at time t, $P_t\, Q_t\, K_{t+1}/N_{t+1}$. Given our conventions, both are either observed or determined by all parties at time t. Therefore, equation (39) implies that with the information available at time t, entrepreneurs expect capital returns equal to

$$P_t Q_t K_{t+1} E_t(R^e_{t+1}) f(\bar{\omega}_{t+1}, s_{t+1}). \tag{A6}$$

Similarly, equation (41) implies that with the information available at time t, lenders expect income equal to

$$P_t Q_t K_{t+1} E_t(R^e_{t+1}) g(\bar{\omega}_{t+1}, s_{t+1}). \tag{A7}$$

The formal contracting problem reduces to choosing the quantity of physical capital, K_{t+1}, and the threshold, $\bar{\omega}_{t+1}$, that maximize the entrepreneurs' expected nominal return on capital net of loan costs (see equations A6 and A4). That is,

$$P_t Q_t K_{t+1} E_t(R^e_{t+1}) \left[1 - J(s_{t+1}) - \Gamma(\bar{\omega}_{t+1}, s_{t+1})\right], \tag{A8}$$

subject to the participation constraint for the lenders (see equations A7 and A3). That is

$$\begin{aligned} &P_t Q_t K_{t+1} E_t(R^e_{t+1}) \left[\Gamma(\bar{\omega}_{t+1}, s_{t+1}) - \mu G(\bar{\omega}_{t+1}, s_{t+1})\right] \geq I^b_{t+1} L_{t+1} \\ &= I^b_{t+1}(P_t Q_t K_{t+1} - N_{t+1}), \end{aligned} \tag{A9}$$

where the equality on the right-hand side follows from equation (32). It is implicitly agreed that if lenders participate in this contract, they always supply enough loans, L_{t+1}, as long as a noncontingent participation rate, I^b_{t+1}, is guaranteed to them in expectation. In other words, we do not explicitly consider the possibility of credit rationing, while we view the (risk-neutral) banks as bearing part of the aggregate risk. All banks share equally in the aggregate size of the loan.

The first-order condition with respect to $\bar{\omega}_{t+1}$ defines the function $\lambda_{t+1} \equiv \lambda(\bar{\omega}_{t+1}, s_{t+1})$ in the following terms:

$$\Gamma_1(\bar{\omega}_{t+1}, s_{t+1}) - \lambda(\bar{\omega}_{t+1}, s_{t+1})\left[\Gamma_1(\bar{\omega}_{t+1}, s_{t+1}) - \mu G_1(\bar{\omega}_{t+1}, s_{t+1})\right] = 0, \tag{A10}$$

where λ_{t+1} is the Lagrange multiplier on the lenders' participation constraint. By virtue of this optimality condition, we say that the shadow cost of enticing the participation of the lenders in this contract is given by

$$\lambda(\bar{\omega}_{t+1}, s_{t+1}) = \frac{\Gamma_1(\bar{\omega}_{t+1}, s_{t+1})}{\Gamma_1(\bar{\omega}_{t+1}, s_{t+1}) - \mu G_1(\bar{\omega}_{t+1}, s_{t+1})}, \tag{A11}$$

which, in turn, implies that the participation constraint must be binding since the multiplier is nonzero. The binding participation constraint can be rewritten as

$$\frac{P_t Q_t K_{t+1}}{N_{t+1}} E_t\left(\frac{R^e_{t+1}}{I^b_{t+1}}\right)\left[\Gamma(\bar{\omega}_{t+1}, s_{t+1}) - \mu G(\bar{\omega}_{t+1}, s_{t+1})\right] = \left(\frac{P_t Q_t K_{t+1}}{N_{t+1}} - 1\right), \tag{A12}$$

or, more compactly,

$$\frac{P_t Q_t K_{t+1}}{N_{t+1}} = \frac{1}{1 - E_t\left(\frac{R^e_{t+1}}{I^b_{t+1}}\right)\left[\frac{\Psi(\bar{\omega}_{t+1}, s_{t+1}) + J(s_{t+1}) + \Gamma(\bar{\omega}_{t+1}, s_{t+1}) - 1}{\lambda(\bar{\omega}_{t+1}, s_{t+1})}\right]}, \tag{A13}$$

where we define $\Psi(\bar{\omega}_{t+1}, s_{t+1})$ as,

$$\begin{aligned}\Psi(\bar{\omega}_{t+1}, s_{t+1}) \equiv\ & 1 - J(s_{t+1}) - \Gamma(\bar{\omega}_{t+1}, s_{t+1}) \\ & + \lambda(\bar{\omega}_{t+1}, s_{t+1})\left[\Gamma(\bar{\omega}_{t+1}, s_{t+1}) - \mu G(\bar{\omega}_{t+1}, s_{t+1})\right].\end{aligned} \tag{A14}$$

The optimization also requires the following first-order condition with respect to capital, K_{t+1}, to hold:

$$E_t\left(\frac{R^e_{t+1}}{I^b_{t+1}}\right)\Psi(\bar{\omega}_{t+1},s_{t+1})-\lambda(\bar{\omega}_{t+1},s_{t+1})=0, \tag{A15}$$

where we implicitly use the conjecture that $\bar{\omega}_{t+1}$ is conditioned on variables known at time t. Simply rearranging gives us the following expression:

$$E_t\left(\frac{R^e_{t+1}}{I^b_{t+1}}\right)=\frac{\lambda(\bar{\omega}_{t+1},s_{t+1})}{\Psi(\bar{\omega}_{t+1},s_{t+1})}, \tag{A16}$$

which determines the excess returns per unit of capital above the participation returns on bank loans that would be required to make the financial contract worthwhile to both entrepreneurs-borrowers and banks-lenders.

If we combine equations (A16) and (A13), then it immediately follows that

$$\begin{aligned}\frac{P_tQ_tK_{t+1}}{N_{t+1}}&=\frac{1}{1-\dfrac{\lambda(\bar{\omega}_{t+1},s_{t+1})}{\Psi(\bar{\omega}_{t+1},s_{t+1})}\left[\dfrac{\Psi(\bar{\omega}_{t+1},s_{t+1})+J(s_{t+1})+\Gamma(\bar{\omega}_{t+1},s_{t+1})-1}{\lambda(\bar{\omega}_{t+1},s_{t+1})}\right]}\\&=\frac{1}{1-\left\{\dfrac{\Psi(\bar{\omega}_{t+1},s_{t+1})+\Gamma(\bar{\omega}_{t+1},s_{t+1})-\left[1-J(s_{t+1})\right]}{\Psi(\bar{\omega}_{t+1},s_{t+1})}\right\}},\end{aligned} \tag{A17}$$

which validates our conjecture on the threshold, implying that

$$\bar{\omega}_{t+1}\equiv\bar{\omega}\left(\frac{P_tQ_tK_{t+1}}{N_{t+1}},s_{t+1}\right).$$

Given the relationships in equations (A16) and (A17), a formulation for the external financing premium arises in the following terms:

$$E_t\left(\frac{R^e_{t+1}}{I^b_{t+1}}\right)=s\left(\frac{P_tQ_tK_{t+1}}{N_{t+1}},s_{t+1}\right). \tag{A18}$$

This characterization of the external financing premium expands the Bernanke-Gertler-Gilchrist framework by adding the explicit possibility that the spread itself be affected by the impact of an anticipated aggregate shock, s_{t+1}. The participation return on loans is set at the time the contract is signed, so I^b_{t+1} is known at time t and can be taken out of the expectation. That is,

$$E_t(R^e_{t+1}) = s\left(\frac{P_t Q_t K_{t+1}}{N_{t+1}}, s_{t+1}\right) I^b_{t+1}. \tag{A19}$$

This relationship is the key feature of the financial accelerator model.

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Household Financial Vulnerability

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Household indebtedness in Chile has received considerable attention in recent years because of the financial deepening process underway in the economy. Although various macroeconomic indicators show significant increases in the last decade, there are few tools for evaluating the real vulnerability of this sector from a financial stability perspective. One of these tools is stress testing using microeconomic information.

Although households may face a variety of financial risks from a range of sources, the household sector is most sensitive to changes in household income, such as those caused by unemployment (Debelle, 2004a, 2004b). Moreover, household vulnerability to aggregate shocks that raise the unemployment rate will depend on both debt distribution and household characteristics. The heterogeneity of indebtedness levels and income uncertainty calls for microeconomic analysis.

The main objective of this paper is to carry out a household stress test at the microeconomic level that allows quantifying household debt at risk when facing aggregate shocks. Evidence from debt issuers indicates that the main reason for households to default is unemployment, so we focus on labor income risk associated with the

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probability of job loss when the aggregate unemployment rate shifts. For this purpose, we use panel data survival analysis to estimate the probability of job loss at the individual level. We then run Monte Carlo simulations to assess household financial stress by estimating aggregate debt at risk under high unemployment rate scenarios.

Financial data at the household level are scarce, which is one of the reasons why there are so few household-level studies assessing household financial indebtedness. The recent Chilean Household Financial Survey (EFH) carried out by the Central Bank of Chile contributes novel information for this type of analysis.

Nordic countries have been leading this sort of analysis The Swedish Central Bank has published a series of simulations based on microeconomic data.[1] They find that Swedish households are not particularly vulnerable to shifts in interest rates or unemployment rates. Specifically, 6.3 percent of households have what they call a negative margin, accounting for 5.6 percent of total household debt (debt at risk). Unemployment rate increases of 1–3 percentage points cause the share of households without a margin to rise to 6.7 percent and debt at risk to 6.3 percent. Vatne (2006) carries out a similar exercise, finding that 19 percent of households have a negative margin and that they account for 16 percent of total debt. The study concludes that low and median income groups hold the majority of the exposed debt and have increased their share over time.

Neither study, however, takes into account that aggregate unemployment does not have a uniform impact on agents across households. In fact, they consider that the probability of falling into unemployment is uniform for all workers. This is a very strong assumption and can bias the results depending on the distribution of debt among individuals. In Chile, there is evidence that unemployment is less frequent within high education groups and among middle-aged workers (Neilson and Ruiz-Tagle, 2007), supporting heterogeneous responses.

The remainder of the paper is organized as follows. Section 1 analyses the distribution of household indebtedness in Chile and discusses debt at risk using data from the 2007 Household Financial Survey. Section 2 estimates job loss probabilities based on data from the Social Protection Survey Panel, covering a ten-year period from 1995 to 2004. Nonparametric and semiparametric methods are used to

1. See Johansson and Persson (2006) and Gyntelberg, Johansson, and Persson (2007).

estimate the impact of aggregate unemployment rates on individual job loss probabilities. Section 3 carries out simulations of debt at risk under different scenarios. For this purpose, job loss probabilities are imputed into the EFH data, and then Monte Carlo simulations are run to assess the distribution of the stress test. Finally, section 4 concludes.

1. Household Indebtedness and Debt at Risk

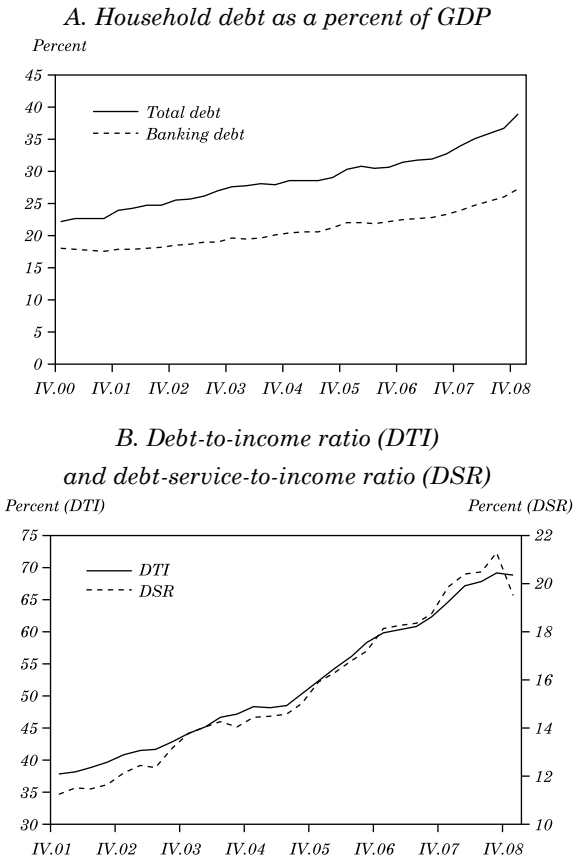
Household borrowing has grown considerably in Chile, both in absolute terms and relative to household income. In fact, the growth rate of debt has consistently surpassed that of real GDP over the last decades. This has raised concerns about the household sector's vulnerability and possible implications for the stability of the financial system. Households' ability to pay back debts and the amount of debt they hold determine how much of this debt could be considered at risk of not being recovered by credit issuers.

Bank debt represents more than 70 percent of total household debt (see figure 1) and grew almost 15 percent, on average, in real annual terms between 2003 and 2008. Real bank debt thus almost doubled during this period, while real GDP increased almost 30 percent. Moreover, the growth of total household debt surpassed the growth of households' disposable income, causing the debt-to-disposable-income ratio to grow significantly over the last several years. In the fourth quarter of 2008, this aggregate indicator reached almost 69 percent, from 44 percent in the fourth quarter of 2003. Furthermore, the ratio of the household financial burden to disposable income also expanded, rising from 14 percent to 20 percent in the same period (figure 1).

Since bank debt is by far the most important household debt, the financial system's exposure to the household sector is a matter of concern from a financial stability perspective. Bank exposure, measured as the share of total mortgage and consumer loans in total bank loans, increased from 15 percent at the beginning of the 1990s to more than 33 percent in 2008.

Although Chilean households are increasing their debt, the trend in Chile is not significantly different from other countries. In fact, the relationship between household debt to GDP and per capita GDP suggests that household debt is not a significant share of GDP. Nevertheless, the financial-burden-to-disposable-income ratio is not particularly low given the country's economic development, measured as per capita GDP (see figure 2). This last observation

Figure 1. Chilean Household Indebtedness at the Macroeconomic Level



Source: Central Bank of Chile.

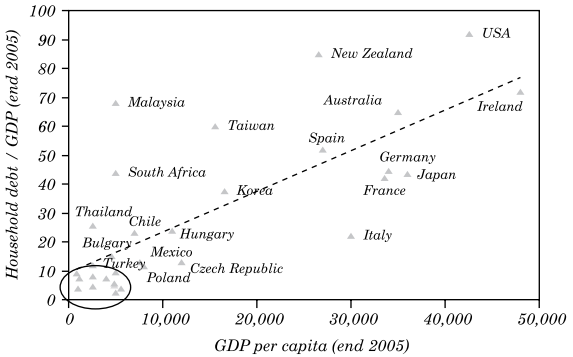
is related to the length of the loans and the high interest rates, relative to developed economies.[2]

Microeconomic analysis reveals an important heterogeneity among Chilean households. In particular, the vast majority of debt is held by high-income groups. This is particularly important in

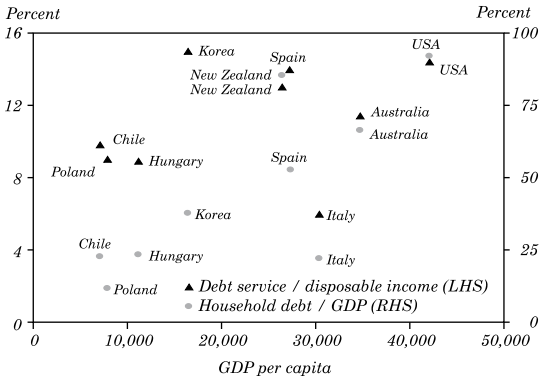
2. There is a caveat about the financial burden. In some countries, debt service refers only to interest payments, while others (including Chile) define it to include both interest and principal payments.

Figure 2. Household Debt: International Comparison

A. Household debt and economic development[a]



B. DSR and household debt



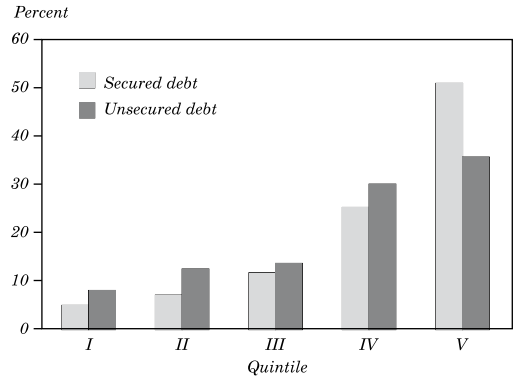
Source: IMF *Global Financial Stability Report* 2006.
a. The countries inside the circle are Argentina, Brazil, China, Colombia, India, Indonesia, Peru, Philippines, Romania, Russia, Turkey, and Venezuela.

Chile because of the high levels of income inequality. In fact, debt distribution maps rather well with income distribution.

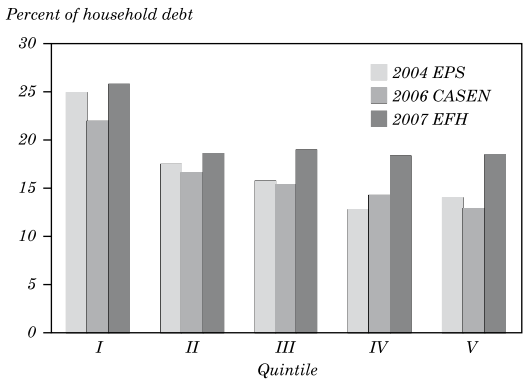
Different microeconomic surveys find a similar pattern, though it may be changing slightly over time, suggesting a financial deepening process (see figure 3; see also figure A1 in the appendix). Moreover, households' behavior in terms of their ability to pay back debts may vary considerably depending on their debt and income levels. This is an important reason to consider household heterogeneity when analyzing household financial vulnerability.

Figure 3. Chilean Household Indebtedness at the Microeconomic Level

A. Distribution of debt by income quintile: 2007 EFH



B. DSR by income quintile



Source: Authors' calculations, based on data from the 2004 EPS, 2006 CASEN, and 2007 EFH.

In the remainder of this section, we describe our data sets and discuss the debt-at-risk methodology used.

1.1 The Chilean Household Financial Survey

Assessing household financial vulnerability requires detailed financial data at the household level. The recent Chilean Household Financial Survey (*Encuesta Financiera de Hogares*, or EFH), contributes with novel information for this type of analysis.

The EFH was conducted by the Central Bank of Chile for the first time in 2007. This survey includes detailed questions about labor status, real estate ownership, financial assets, debt, perceptions of debt service, access to credit, pensions, insurance, and savings. The 2007 EFH covered 4,021 households and was representative at the national urban level. Furthermore, since a small fraction of the population holds a large share of assets, the survey oversampled wealthier households. This skew in the sample was possible thanks to the collaboration of the Chilean Internal Revenue Service. The 2007 EFH thus constitutes the only statistical source in Chile that provides complete information on household balance sheets and their ability to service financial commitments.[3]

1.2 Debt Distribution and Debt at Risk

There is no common definition of debt at risk. The Central Bank of Chile uses a definition based on the ratio of debt service over income (that is, the debt service ratio, or DSR).[4] Norway and Sweden consider negative margins (that is, when total spending exceeds total income). They also include liquid and illiquid assets as debt backup. For household h, the margin is computed as

$$M_h = Y_h - DS_h - E_h, \tag{1}$$

where Y_h is total household income, DS_h is debt service, and E_h is total household expenditures.

In this paper, the baseline scenario of debt at risk is built considering two dimensions: a negative financial margin and a high DSR. Data collection posses two problems for interpretation. First, there is a risk of double counting. For example, clothing expenditures could also appear as debt if purchased with a credit card. Second, if

3. For a description of the 2007 Chilean Household Financial Survey and a discussion of the methodology and results, see Central Bank of Chile (2009).

4. See Cox, Parrado, and Ruiz-Tagle (2006).

a significant share of total expenditures is made with credit cards (including supermarket expenditures, for example), the DSR indicator could actually overestimate the financial stress of the households.

Taking into account these caveats, we build our baseline scenario for debt at risk considering both a negative financial margin and a high DSR. The negative financial margin is set at 20 percent excess expenditure over income, and the DSR is considered high when it is above 50 and above 75. Table 2 presents results for the baseline scenario of debt at risk based on the debt service ratio and the financial margin. The table reveals that 13.6 percent of households exhibit a negative margin and a DSR larger than 50 percent, accounting for 20 percent of total debt. A more refined assessment of debt at risk, with the DSR above 75 percent, indicates that 9.5 percent of households are highly financial stressed and 16 percent of total debt is at risk (15 percent of secured debt and 19 percent of unsecured debt).

2. Assessing Financial Vulnerability

Household financial vulnerability in Chile is mainly due to income sources, since only a negligible share of household debt has a variable interest rate. Households' main income source is the labor income of their members.[5] Labor income can be lost if the job ends for any reason, whether voluntary or involuntary. At any time, workers face a given probability of losing their jobs. By imputing these job loss probabilities to working individuals, we can assess their financial vulnerability, provided the financial information is available. However, there are no available estimates of job loss probabilities in Chile.[6] This section therefore provides estimates of job loss probabilities based on survival analysis using nonparametric and semiparametric methods. In particular, the interest is focused on the effect of aggregate unemployment rate on job loss probabilities.

The effects of aggregate unemployment are heterogeneous in both a static and dynamic framework. Given that the distribution of household debt is diverse, the impact of higher unemployment levels generates nonhomogeneous effects on debt at risk. The Norwegian and Swedish studies propose a simplified analysis assuming that unemployment

5. Neilson and others (2008) document that labor dynamics is the main factor driving entry and exit from income-stressing conditions. In the EFH, labor income accounts for more than 60 percent of total households income.

6. There are only estimates of unemployment duration.

shocks affect all individuals in the same manner. Although limited, that methodology makes sense for them because the distribution of debt in those countries is much flatter than in Chile (particularly in Norway), and also because they have large unemployment benefits that cover a substantial part of lost income for a long period. In contrast, for Chile it is more appropriate to estimate disaggregated job loss probabilities to assess heterogeneous impacts.

2.1 Job Loss Probability

Estimating job loss probabilities requires survival analysis. In this case, job loss probability mirrors the probability of staying employed. What is estimated, then, is the probability of remaining employed (or surviving, in the analysis) at a given moment of time t.

Let T be a nonnegative random variable denoting the time to failure (in this case, failure is job loss). The survival function is the reverse of the cumulative distribution function of $T[F(t)]$:

$$S(t) = 1 - F(t) = \Pr(T > t). \tag{2}$$

It reports the probability of surviving beyond time t, where the density function is simply $f(t) = -S'(t)$.

The cumulative hazard function is defined as

$$H(t) = -\ln[S(t)], \tag{3}$$

such that

$$f(t) = h(t)\exp[-H(t)]. \tag{4}$$

For the purpose of this paper, what is interesting is how some covariates affect the hazard function, which requires multivariate analysis. Nevertheless, simpler nonparametric analysis can be used to compare different groups' hazard functions. This is done by estimating the survival function through the Kaplan-Meier (1958) estimator, given by

$$\hat{S}(t) = \prod_{j|t_j \le t} \left(\frac{n_j - d_j}{n_j} \right), \tag{5}$$

where n_j is the number of individuals at risk at time t_j and d_j is the number of failures at time t_j.

The Cox (1972) semiparametric model requires no parametric form of the survival function. It assumes that covariates shift multiplicatively the baseline hazard function. For the jth subject, the hazard function is:

$$h(t|\mathbf{X}_{j,t}) = h_0(t)\exp(\mathbf{X}_{j,t}\beta_x), \tag{6}$$

where $\mathbf{X}_{j,t}$ is a vector of variables, and the values of β_x are estimated from the data.

The baseline function $h_0(t)$ is not parameterized (or even estimated), because the model is proposed in terms of ratios (individual j compared with individual m):

$$\frac{h(t|\mathbf{X}_{j,t})}{h(t|\mathbf{X}_{m,t})} = \frac{\exp(\mathbf{X}_{j,t}\beta_x)}{\exp(\mathbf{X}_{m,t}\beta_x)}. \tag{7}$$

The Cox model is rather convenient for the purpose of this paper, because it is easy to compute and can provide predicted probabilities given the covariates.

Parametric methods require imposing a functional form to the baseline hazard function. The most common are the Weibull, exponential, lognormal, gamma and log-logistic models. These models are computationally costly, and they also have the disadvantage of bias in case of an inappropriate distributional assumption.

This papers combines different nonparametric, semiparametric, and parametric methods to accurately predict job loss probabilities.

2.2 The Data

The Social Protection Survey (*Encuesta de Protección Social*, EPS) has been carried out in Chile every two years since 2002. This panel survey was designed to assess the well-being of workers and nonworkers and their households.[7] The EPS includes 16,727 observations, representing the population of Chile aged 18 and over in 2004.

7. The EPS was designed jointly by the Ministry of Labor and the Centro de Microdatos of the Universidad de Chile, with the close collaboration of the University of Pennsylvania.

In the 2002 wave, the individuals were asked to chronologically list every single labor experience since 1980. Each experience had a beginning date and an ending date. For each experience, the individuals were asked about their employment status, the characteristics of the job, and some qualitative questions. In the 2004 wave, individuals were asked to provide the missing history, that is, the experiences that occurred between 2002 and 2004.

The data are then organized into a monthly panel of individuals with the corresponding employment information in each period. This gives us the employment status of a sample that is representative of the Chilean population aged 18 and more in 2004. Representativeness in past years narrows to a varying age group. For instance, in 2004 the data are representative of people between 18 and 65 years old, in 2003, between 18 and 64 years old, and so on.

In this paper, we use a ten-year period from 1995 to 2004. This period comprises the Asian crisis and a relatively short mild recession in 1999 and 2000. Consequently, the unemployment rate rose significantly and remained high for a long period afterward. Given this timeframe, the sample covers 16,727 individuals over 120 months, which implies that the data set has around two million records.

2.3 Estimation Results

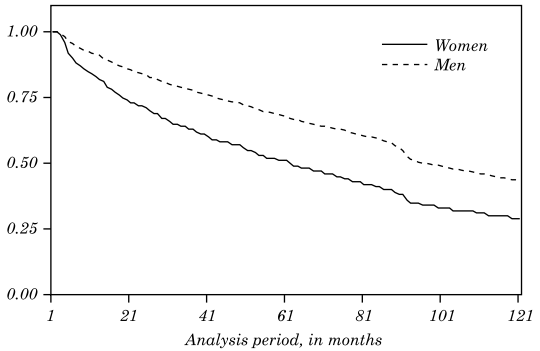
We estimate job loss probabilities using the labor experiences reported in the 2002 and 2004 EPS. The probabilities incorporate a set of individual characteristics, $\mathbf{X}_{jt}$, and a set of time variant aggregate variables, $\mathbf{Z}_{jt}$. The $\mathbf{X}_{jt}$ vector of variables includes gender, age, education, job contract, marital status, economic sector of the job, and size of the firm. The $\mathbf{Z}_{jt}$ vector considers the aggregate unemployment rate and monthly activity indexes.

We define job loss as any exit from a job resulting in unemployment of inactivity. This definition reflects our objective of assessing households' ability to cope with their financial obligations, since any decay in income will increase household financial stress.

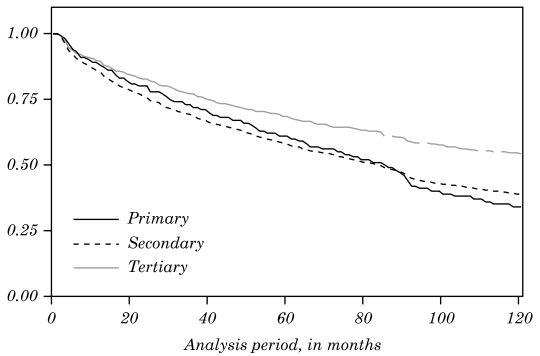
To assess survival heterogeneity, we first look at the Kaplan-Meier nonparametric estimates of the survival functions. Figure 4 presents estimates of the survival function by gender and educational level. Men are less likely to lose employment than women at any time: the mean estimator indicates that men remain employed 50 percent longer than women, and the probability of losing employment reaches 50 percent only after 80 months for both genders. Workers with tertiary

Figure 4. Job Loss Probabilities

A. Kaplan-Meier survival estimates by gender



B. Kaplan-Meier survival estimates by education level



Source: Authors' calculations, based on data from the 2002 and 2004 EPS.

education have a much lower probability of losing employment than those with primary and secondary education. Workers with secondary education have a larger job loss probability than those with primary education at shorter employment durations and a lower job loss probability after 90 months.

Next, we carried out multivariate analysis for multiple specifications using the Cox semiparametric estimates of the proportional hazard model. Table 1 presents our preferred model. A series of interesting results emerge from the data. First, the job loss probability of men is around 30 percent lower probability than women. The unemployment rate shifts that probability by 17 percent,

Table 1. Cox Estimations of Job Loss Probabilities

Variable	*Hazard ratio*	*z*	*P*> |*z*|	*95% confidence interval*
Males = 1	0.333	–15.46	0	0.289
	(0.024)			(0.382)
Age	0.866	–27.15	0	0.857
	(0.005)			(0.875)
Age squared	1.001	22.28	0	1.001
	(0.000)			(1.001)
Unemployment rate	1.121	22.11	0	1.110
	(0.006)			(1.133)
Unemployment rate *(Males = 1)	1.065	10.23	0	1.052
	(0.007)			(1.078)
Unemployment rate *(Secondary ed. = 1)	0.961	–22.12	0	0.957
	(0.002)			(0.964)
Unemployment rate *(Tertiary ed. = 1)	0.977	–5.15	0	0.968
	(0.004)			(0.986)
Summary statistic				
No. subjects	12,906			
No. failures	10,907			
No. observations	1,295,487			
Time at risk	1,301,439			
Log likelihood	–99,708.4			
LR chi squared (7)	3,661.31			

Source: Authors' calculations.
a. Coefficients are in exp(β) form. Standard errors are in parentheses.

but it seems to have a much larger effect on men than women (around 8 percent per unemployment percentage point).

Second, age has a decreasing negative effect on job loss probabilities. This means that younger workers are much more likely to lose employment at any given time than older workers, but the effect fades as age increases.

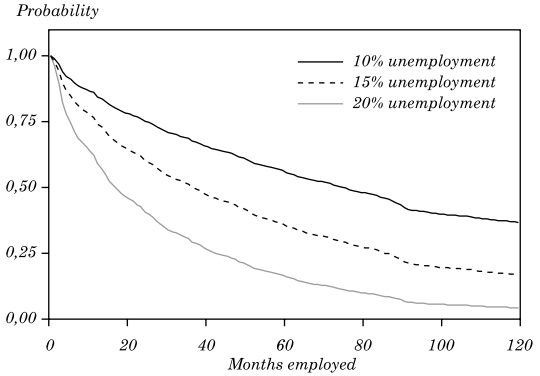
Third, workers with higher levels of education face a significantly lower probability of losing their jobs. Those with tertiary education have about a 30 percent lower probability than those with

primary education only. The effect of the unemployment rate is also heterogeneous among different education groups. Workers with tertiary education have a 5 percent lower probability per unemployment percentage point (implying about 45 percent lower probability, on average) than those with primary education only. Workers with secondary education face a 3 percent lower probability per unemployment percentage point (implying about 27 percent lower probability on average) than those with primary education only.

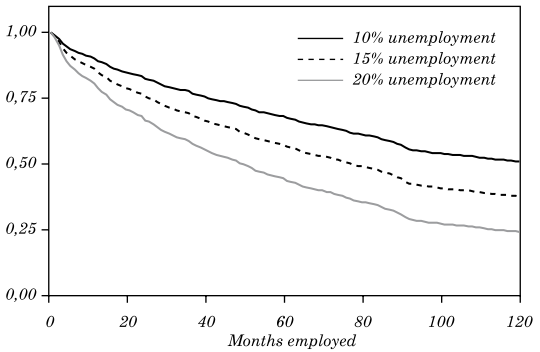
From the Cox estimates, we can predict job loss probabilities through the survival functions. Figures 5 and 6 show the survival function estimates for women and men, respectively. Age was set at mean values (around 41 years old), and unemployment shifts were set at 10 percent, 15 percent, and 20 percent. It is clear from the graphs that higher educational attainment diminishes job loss probabilities and, more importantly for our purposes, also diminishes the impact of an aggregate unemployment shift. Women exhibit higher probabilities of job loss (the survival functions are lower), but aggregate unemployment shifts affect men considerably more than women.

Figure 5. Job Loss Probabilities for Women, by Education level

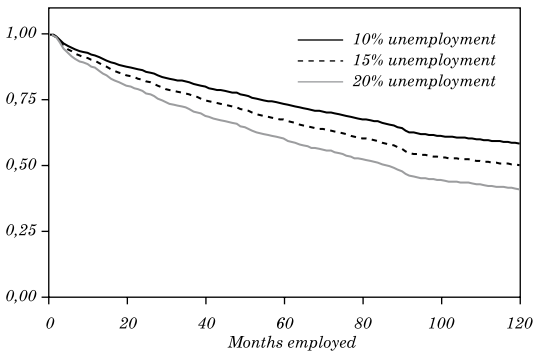
A. Survival function: Women with primary education



B. Survival function: Women with secondary education



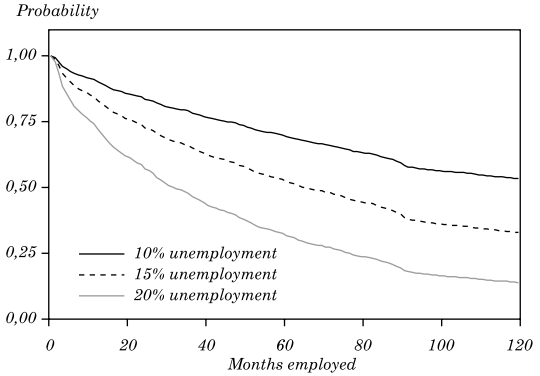
C. Survival function: Women with tertiary education



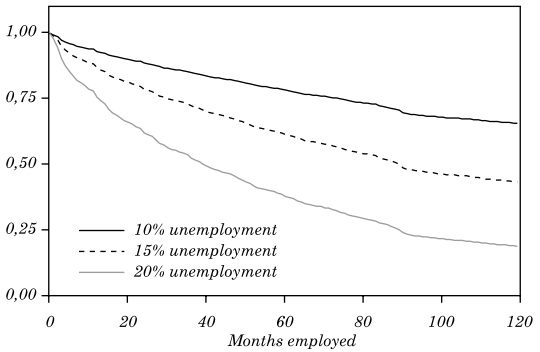
Source: Authors' calculations, based on data from the 2002 and 2004 EPS.

Figure 6. Job Loss Probabilities for Men, by Education level

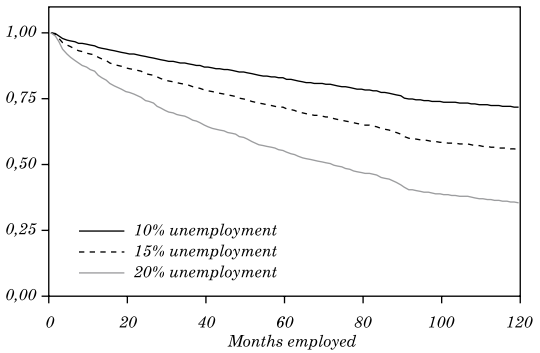
A. Survival function: Men with primary education



B. Survival function: Men with secondary education



C. Survival function: Men with tertiary education



Source: Authors' calculations, based on data from the 2002 and 2004 EPS.

3. Financial Stress Simulation

This section is devoted to the analysis of higher unemployment rates simulations and their effects on debt at risk. We ran Monte Carlo simulations on the probability of losing employment for each of the worker individuals in each household. We then imputed the employment loss probabilities determined earlier to the EFH data set.

The first problem for this exercise is that the EFH does not contain information about employment duration. Employment loss probabilities depend critically on the duration of the job, so we had to impute employment duration. To do so, we separated workers into cells by age group and educational attainment. For each cell, the whole distribution of employment duration was computed as $\hat{d}_c$. Then, every worker j in cell c was assigned a random employment duration following the actual distribution $\tilde{d}_c \sim \hat{d}_c$. Hence, this is the first source of randomization.[8]

We then ran the simulations as follows. First, we assigned a uniform random number u_{jh} to each worker in the EFH. For each worker in the EFH with an assigned employment duration $\tilde{d}_c$ with characteristics $\mathbf{X}_{jh}$ and under the scenario given by $\mathbf{Z}^t$, we computed a job loss probability using the estimated parameters from the hazard function. If that probability is below the threshold given by the random number, the worker is considered to be employed. If not, the worker is considered to have lost his or her employment, so labor income in this case becomes zero.

$$\hat{Y}_{jh}^t = Y_{jh}^t \times 1\left[\hat{\Pr}_{jh}^t(\mathbf{X}_{jh}^t, \mathbf{Z}^t) > u\right]. \tag{8}$$

The second source of randomization comes from the fact that the simulated employment loss probability contains the uncertainty with respect to the survival model estimate through the probability of losing the job.

After the worker's employment condition of the worker is redefined and the corresponding labor income recomputed, overall household income is computed again. The DSR must also be refreshed to reflect the simulated total household income. Finally, aggregate indicators of debt at risk are computed again for the whole sample.

8. For the simulations, the actual cumulative density function, $\Phi\hat{d}_c$, was approximated by a nine-degree polynomial. Figures A2 and A3 in the appendix show those estimates.

In the baseline scenario, 61 percent of total households hold some sort of formal debt. Specifically, 16 percent of households hold secure debt, and 57 percent hold unsecured debt. Secure debt is 60 percent of total debt (unsecured debt is 40 percent). Moreover, 45 percent of total debt is held by the upper richest quintile (51 percent of secure debt and 36 percent of unsecured debt). The median DSR is 19.5 percent for all indebted households.

Table 2 presents the results of the simulations.[9] In the baseline scenario, with the DSR above 75 percent and the negative margin above 20 percent, 9.5 percent of households are considered to have debt at risk. Those households accounts for 16.1 percent of total household debt.

We then use the underlying job loss probabilities to expand the current debt at risk to include households whose members could lose their jobs at any moment, thus falling into higher financial stress. This raises the number of households under financial stress to between 13 percent and 16 percent, while total debt at risk increases to between 20 percent and 25 percent, with a 95 percent confidence interval.[10]

Next, we increase the unemployment rate by 5 percent. This is a larger increase than occurred during the Asian crisis. Under this scenario, the number of households under high financial stress increases to between 16 percent and 19 percent, and debt at risk rises to between 22 percent and 28 percent. A 15 percent increase in unemployment increases the number of highly stressed households to between 25 percent and 28 percent, and debt at risk to between 31 percent and 38 percent. These results indicate that significant increases in the aggregate unemployment rate do not necessarily imply a significant increase in debt at risk relative to the current situation.

These results imply that higher levels of unemployment, similar to what was observed during the Asian crisis, do not necessarily generate a significant household default shock in the financial system. In this scenario, debt at risk only increases around 4 percentage points (compared with the baseline scenario including underlying job loss probabilities). Nevertheless, this

9. We used 500 Monte Carlo simulations. Exercises with 1,000 and 5,000 simulations did not produce significantly different results.

10. We built the 95 percent confidence intervals nonparametrically using simulation percentiles.

Table 2. Households with a Negative Margin

Scenario and DSR threshold	*Households*	*Secured debt*	*Unsecured debt*	*Total debt*
Baseline scenario				
DSR > 50	13.6	17.1	26.1	20.2
DSR > 75	9.5	14.5	18.8	16.1
Baseline scenario + underlying job loss probability				
DSR > 50	18.2 – 20.8	20.3 – 26.3	30.8 – 36.5	24.3 – 29.4
DSR > 75	13.2 – 15.6	17.1 – 22.6	23.1 – 29.0	19.7 – 24.6
Delta+ 5% unemployment				
DSR > 50	21.5 – 24.4	22.9 – 30.2	34.1 – 40.4	27.1 – 33.0
DSR > 75	15.9 – 18.8	19.2 – 26.2	26.2 – 33.3	22.3 – 28.1
Delta+ 10% unemployment				
DSR > 50	26.1 – 29.5	26.7 – 35.3	38.7 – 45.6	31.2 – 38.3
DSR > 75	20.1 – 23.3	22.8 – 30.2	30.9 – 38.8	25.9 – 32.6
Delta+ 15% unemployment				
DSR > 50	31.0 – 34.6	31.9 – 40.9	44.3 – 51.4	36.6 – 44.3
DSR > 75	24.5 – 28.0	27.0 – 35.3	36.4 – 44.3	31.0 – 37.9

Source: Authors' calculations.
a. The intervals for the simulations are p(2.5) to p(97.5), and are given in percent.

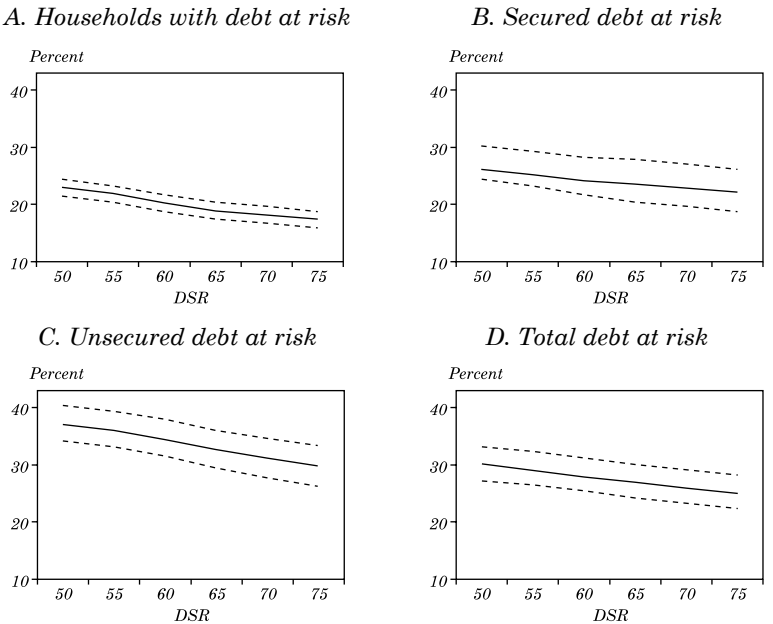
does not mean that the financial system can overlook household debt. Table 2 suggests that for a one-percentage-point increase in the unemployment rate, debt at risk expands between 0.6 and 0.8 percentage points.[11]

The DSR threshold of 75 percent is not very demanding for considering a household under high financial stress. Table 2 includes a 50 percent threshold, and figure 7 complements the analysis by presenting a range of DSR thresholds under an unemployment shift of 5 percent and with the negative margin at 1.2. The results are fairly stable, with no extreme shifts in debt at risk.[12]

11. Jappelli, Pagano, and di Maggio (2008) study a sample of eleven member countries of the European Union. They estimate 0.37 percentage points increase in arrears for each percentage point increase in the unemployment rate.

12. Figure A4 in the appendix presents the exercise with a negative margin of 1.1.

Figure 7. Debt at Risk Simulations at Different DSR Thresholds[a]



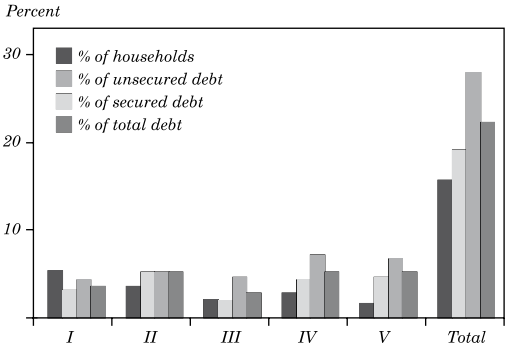
Source: Authors' calculations.
a. Unemployment shift of 5 percent and a negative margin of 1.2.

We also look at the distribution of the effects by income quintiles. Figure 8 presents the baseline scenario plus the extreme scenarios (percentiles 2.5 and 97.5) under a 5 percent increase in the aggregate unemployment rate. When unemployment increases, debt at risk will only increase significantly if the households in the high income quintiles are affected. Our estimates of the job loss probabilities indicate that this is fairly unlikely under all circumstances. However, the bottom line is that high-income, high-debt households should be monitored.

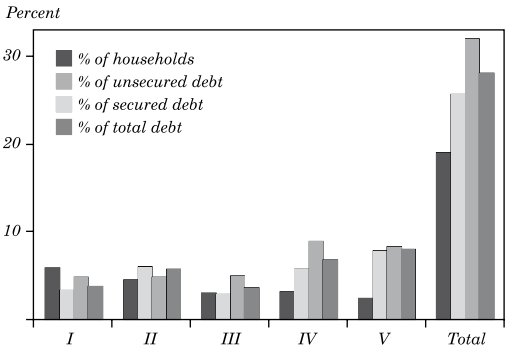
Figure 8. Debt at Risk Simulations by Income Quintile

A. Baseline scenario

B. Scenario: 5 percent increase in unemployment, p(2.5)



C. Scenario: 5 percent increase in unemployment, p(97.5)



Source: Authors' calculations, based on data from the 2002 and 2004 EPS.

Finally, several issues are not considered in this simulation exercise. First, as workers face nonnegative unemployment probabilities, unemployed (and inactive) workers face a nonnegative probability of becoming employed and then being able to contribute labor income to household financial resources. Second, workers who lose their jobs may have unemployment insurance, although in Chile this does not imply a significant source of income.[13] Third, workers who retire to inactivity may have pension income. Fourth, households that experience unemployment may use other sources of income to face their financial obligations, making default less likely to occur. Fifth, households that experience unemployment may sell assets in order to avoid default. Finally, since household-level default data are not available, the increase in debt at risk after a shock should be interpreted as household debt that could come under financial strain, rather than an increase in nonperforming loans. All these caveats go in the same direction, which is to make this simulation exercise less stressing for households' financial situation. Consequently, this exercise should be considered as an upper bound that is unlikely to occur.

4. Conclusions

The indebtedness of the household sector has increased significantly in recent years in Chile. However, no analysis had been carried out previously to assess how vulnerable households could be in terms of their financial stress under aggregate unemployment shifts. This paper contributes with a novel analysis aimed at quantifying the associated risks for financial stability.

Households display significant heterogeneity in terms of the fragility of their main income source, labor income, implying that microeconomic studies must be used to assess aggregate impacts of unemployment on financial stress. Gender, age, and education are the key factors that determine the size of the impact of unemployment shocks on the probability of losing a job.

We find that for a one-percentage-point increase in the unemployment rate, debt at risk increases between 0.6 and 0.8 percentage points. However, because household debt is concentrated in high income households, heterogeneous responses to unemployment may have important implications for financial stability. In fact, the

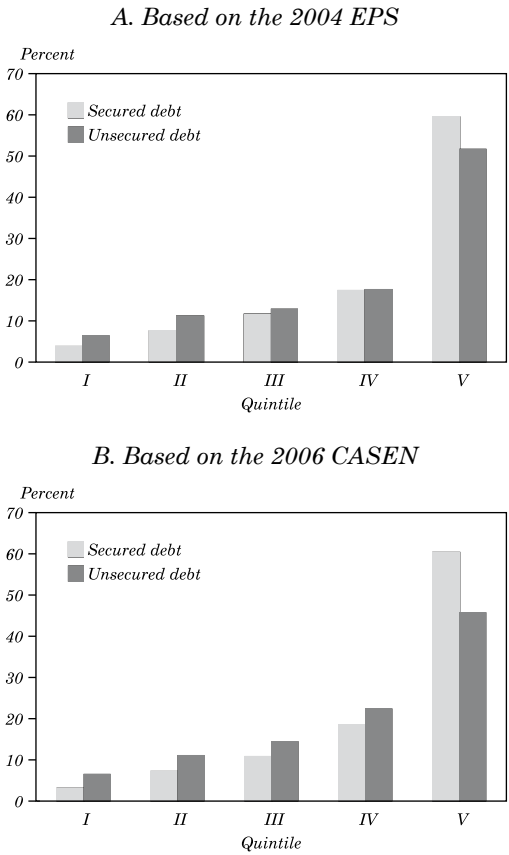
13. Unemployment insurance covers 30 percent of earnings for three months for a worker who has been employed at least 40 consecutive months.

simulations carried out on the different shock scenarios show that debt at risk is rather bounded.

Higher levels of unemployment do not necessarily generate a significant household default shock in the financial system. Nevertheless, this does not mean that the financial system can overlook household debt.

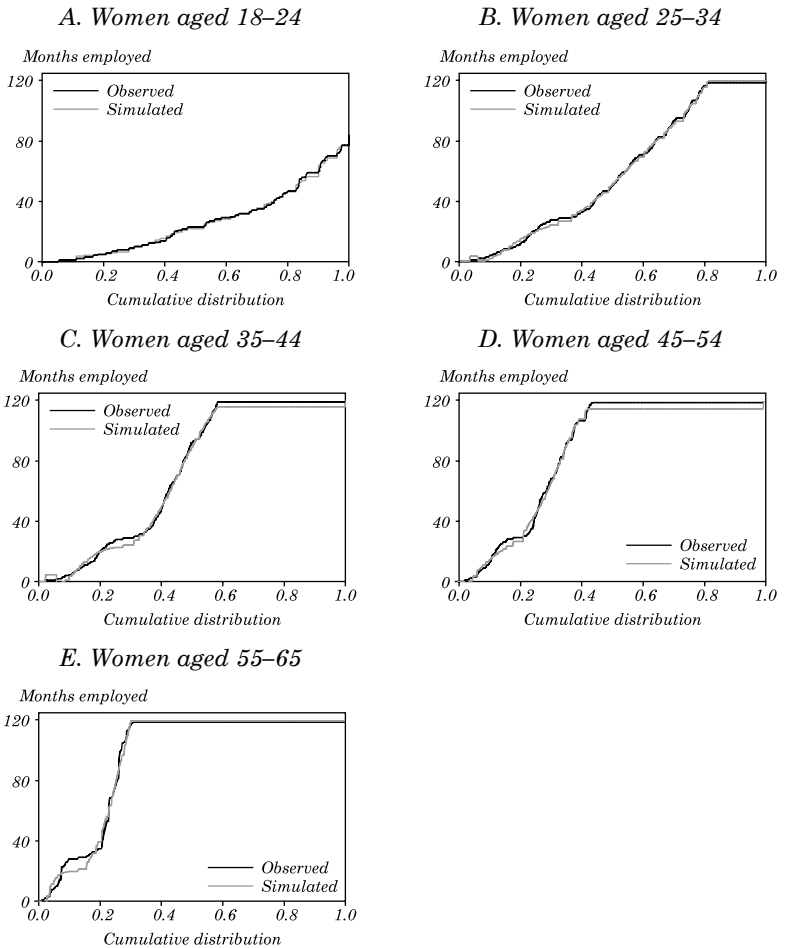
Appendix
Supplemental Figures

Figure A1. Distribution of Chilean Household Indebtedness by Income Quintile



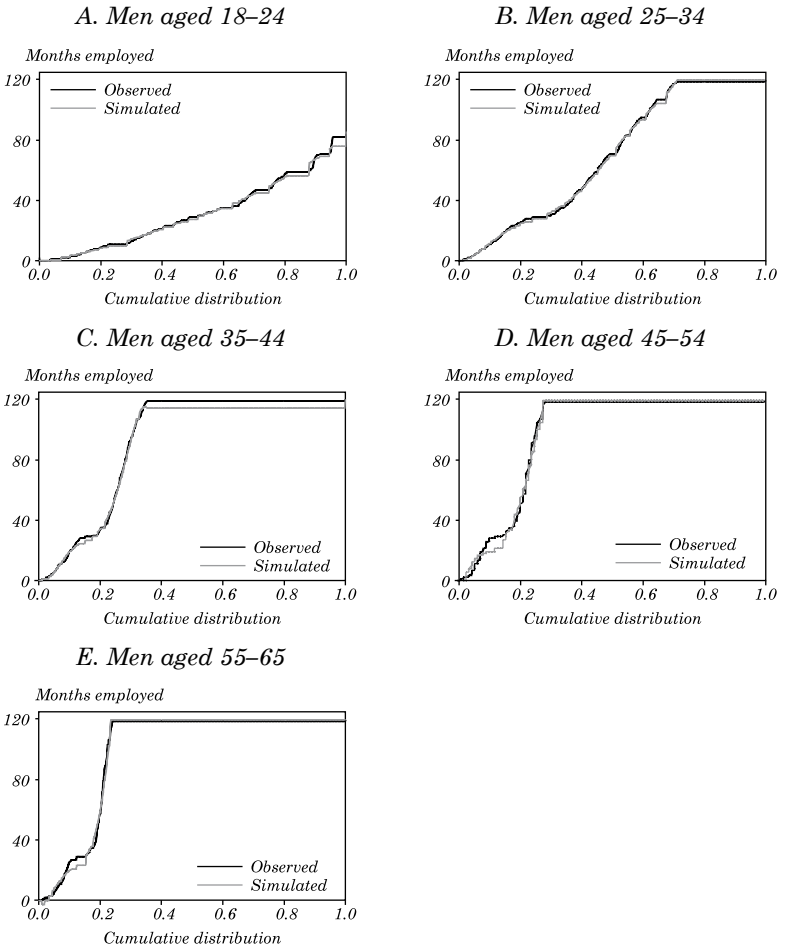
Source: Authors' calculations, based on data from the 2004 EPS and the 2006 CASEN.

Figure A2. Employment Duration Distribution for Women



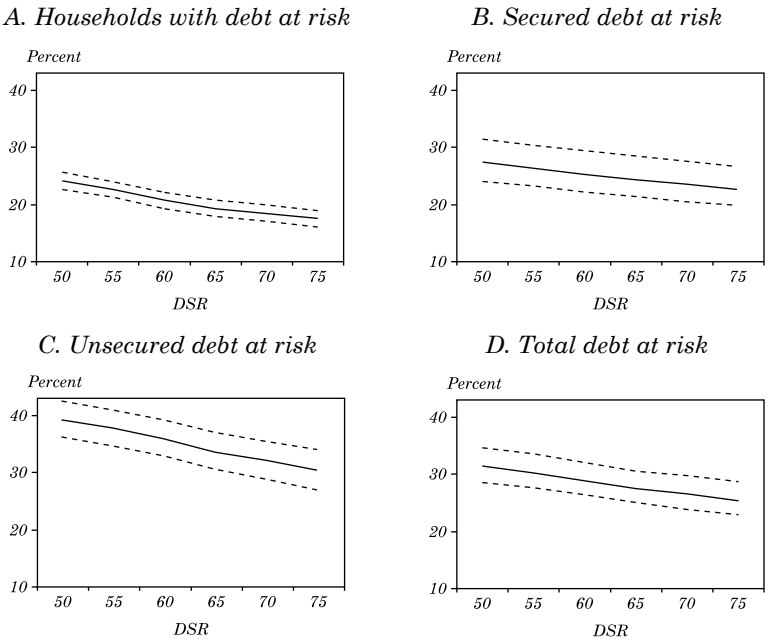
Source: Authors' calculations based on 2002 and 2004 EPS.

Figure A3. Employment Duration Distribution for Men



Source: Authors' calculations based on 2002 and 2004 EPS.

Figure A4. Debt at Risk Simulations at Different DSR Thresholds[a]



Source: Authors' calculations based on 2002 and 2004 EPS.
a. Unemployment shift of 5 percent and a negative margin of 1.1.

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Distress Dependence and Financial Stability

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The proper estimation of distress dependence amongst the banks in a system is key to monitoring the stability of the banking system. Financial supervisors recognize the importance of assessing not only the risk of distress, i.e. large losses and possible defaults by a specific bank, but also the impact that such an event would have on other banks in the system. Clearly, an event involving simultaneous, large losses in several banks would affect the stability of the whole system, and thus represents a major concern for supervisors. Banks' distress dependence is based on the fact that banks are usually linked, either directly, through the inter-bank deposit market and participation in syndicated loans, or indirectly, through lending to the same sectors and proprietary trades. Their distress dependence varies throughout the economic cycle and tends to rise in times of distress, since the fortunes of banks decline concurrently through either direct links, that is, contagion after idiosyncratic shocks, affecting inter-bank deposit markets and participation in syndicated loans, or indirect links, that is, negative systemic shocks, affecting lending to common sectors and proprietary trades. At such times, the banking system's

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joint probability of distress (JPoD, defined as the probability that all banks in the system will experience large losses simultaneously or banks' distress dependence), may experience larger, nonlinear increases than those experienced by the probabilities of distress (PoDs) of individual banks. Consequently, it becomes essential for the proper estimation of the banking system's stability to incorporate banks' distress dependence and its changes across the economic cycle.

Based on Segoviano and Goodhart (2009), in this paper we estimate a set of banking stability measures (BSMs) that express the interdependent structure of bank distress, capturing both linear (correlation) and nonlinear distress dependencies among the banks in the system. Moreover, the structure of linear and nonlinear distress dependencies shifts as banks' probabilities of distress (PoDs) change; hence, the proposed stability measures incorporate changes in distress dependence consistent with the economic cycle. This is a key advantage over traditional risk models, most of which incorporate only linear dependence (correlation structure), assuming it remains constant throughout the economic cycle.[1]

The proposed BSMs represent a set of tools to analyze (define) stability from three different, yet, complementary perspectives, as they quantify: (i) "tail risk" in the banks within a system, (ii) distress between specific banks, and (iii) cascade effects, defined as distress throughout the associated system, triggered by the distress of a specific bank.

As described below, the authors conceptualize the banking system as a portfolio of banks comprising the core banks of systemic importance in any country. We then estimate the banking system portfolio's multivariate density (BSMD), based on which we construct a set of banking stability measures (BSMs). We show how these BSMs can be constructed from a very limited data set, for example, empirical measurements of individual bank distress. Generally speaking, alternative approaches are used, according to data availability. In this case, the authors have opted for a data set that is available in most

1. In contrast to correlation, which only captures linear dependence, copula functions characterize the whole dependence structure; i.e., linear and non-linear dependence, embedded in multivariate densities (Nelsen, 1999). Thus, in order to characterize banks' distress dependence we employ a novel, non-parametric copula approach, the CIMDO copula (Segoviano, 2009), described below. Compared to traditional methodologies used to model parametric copula functions, the CIMDO copula avoids the difficulties of explicitly choosing the parametric form of the copula function to be used, and calibrating its parameters, since CIMDO copula functions are inferred directly (implicitly) from the joint (simultaneous) movements of individual bank PoDs.

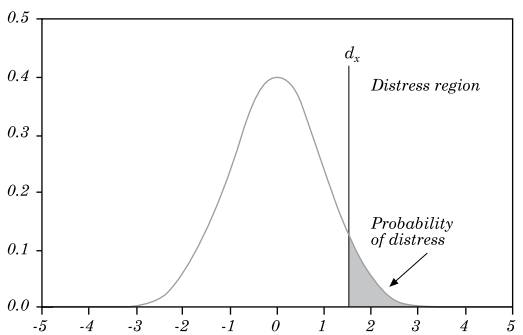
countries to estimate BSMs. Consequently, such measures can be developed for a wide range of developing and developed countries.

In this paper, we also incorporate non-bank financial institutions, whether corporate or sovereign, to facilitate analysis of distress dependence between the banking sector and other sectors. Being able to establish a set of measures with a minimum of basic components facilitates a broader range of comparative analysis, involving both time series and cross-sections. The flexibility of using these measures is relevant to monitoring banking stability, as cross-border financial linkages are becoming increasingly significant, as has been illustrated by the financial market turmoil of recent months. Thus, monitoring banking stability cannot stop at national borders. Section 1 describes how Segoviano and Goodhart (2009) model distress dependence. Section 2 provides a summary of the Banking Stability Measures proposed by the authors. Section 3 shows how these measures can be employed to analyze stability from different perspectives. Finally, section 4 offers our conclusions.

1. Distress Dependence in the Financial System

Quantitative estimation of distress dependence among banks and/or other financial institutions is a difficult task. Information restrictions and difficulties in modeling distress dependence arise due to the fact that distress is an extreme event, which can be viewed as a tail event defined in the distress region of the probability distribution that describes a bank's implied asset price movements (figure 1).

Figure 1. The Probability of Distress



Source: Segoviano and Goodhart (2009).

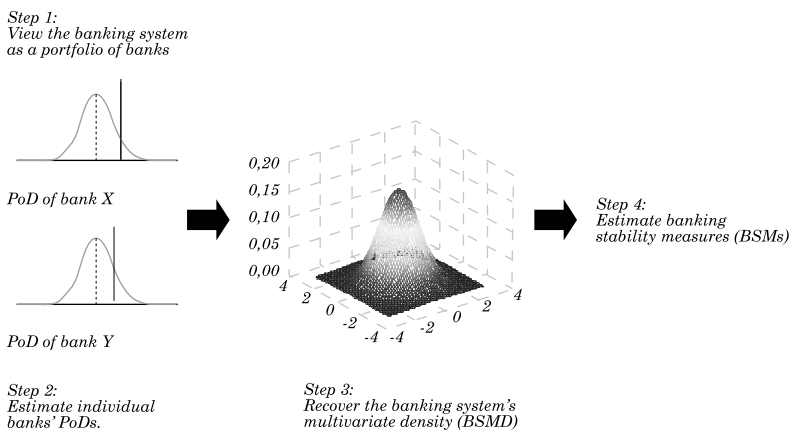
The fact that distress is a tail event makes the often used correlation coefficient inadequate to capture bank distress dependence and the standard approach to model parametric copula functions difficult to implement. In our modeling of banking systems' stability and distress dependence, we replicate Segoviano and Goodhart (2009) and proceed as follows (figure 2):

Step 1: We conceptualize the banking system as a portfolio of banks.
Step 2: For each of the banks included in the portfolio, we obtain empirical measurements of probabilities of distress (PoDs).

Step 3: Using the Consistent Information Multivariate Density Optimizing (CIMDO) methodology, presented in Segoviano (2006) and summarized below, and taking as input variables the individual banks' PoDs, developed in the previous step, we estimate the banking system's (portfolio) multivariate density (BSMD).
Step 4: Based on the BSMD, we estimate the proposed banking stability measures (BSMs).

The banking system multivariate density (BSMD) characterizes both the individual and joint asset value movements of the portfolio of banks representing the banking system (figure 2).

Figure 2. The Banking System's Multivariate Density



Source: Segoviano and Goodhart (2009).

1.1 The Importance of Time-Varying Distress Dependence

We recover the BSMD using the Consistent Information Multivariate Density Optimizing (CIMDO) methodology (Segoviano, 2006b). This offers key technical improvements over traditional risk models that, generally speaking, only account for linear dependence (correlations) assumed to remain constant throughout the cycle or a fixed period of time. The BSMD captures bank distress dependence structure, as characterized by the CIMDO copula function (Segoviano, 2009), in terms of both linear and nonlinear distress dependencies among banks in the system, and allows for these to change throughout the economic cycle, reflecting the fact that distress dependence increases in periods of distress. This implies that systemic risks rise faster than individual risks.

To illustrate this point, for a portfolio of globally active banks we estimate the average probability of default, and the joint probability of default using alternative assumptions to describe the BSMD (a multivariate *t*-density, *t*-JPoD), and the CIMDO density (JPoD).[2] The joint probability of default represents the probability of all the banks included in the portfolio becoming distressed. Accordingly, this is estimated by integrating the alternative BSMD across the region of default of each of the marginal densities that compose them.

Daily percentage changes in the JPoD are larger than daily percentage changes in the average for individual PoDs and the *t*-JPoD. This empirical fact provides evidence that in times of distress, not only do individual PoDs increase (as captured by the three alternative measures), but so does distress dependence (as captured by the JPoD). Therefore, systemic risk may experience larger and nonlinear increases than those for individual bank probabilities of distress (PoDs) and those suggested by a density distribution with fixed correlation parameters. Consequently, measures for financial stability based on averages, or indexes that assume fixed correlation parameters over time could be misleading.

The CIMDO method involves a reduced-form or non-parametric approach to model copulas that seems to adequately capture default dependence and its changes at different points in the economic cycle. This method is easily implementable within the data constraints

2. The degrees of freedom and correlation parameters that characterize the multivariate *t*-density are estimated using empirically observed data.

affecting bank distress dependence modeling and produces robust estimates under the probability integral transformation (PIT) criterion.[3] To show improvements in modeling distress dependence (and therefore in our proposed measures for stability), in the next sections, we (i) model the BSMD using the CIMDO methodology, and (ii) illustrate the advantages embedded in the CIMDO copula as used to characterize distress dependence among banks in the banking system.

1.2 The CIMDO Approach: Modeling Banking System Multivariate Density

We estimate the BSMD using the CIMDO methodology and empirical measures of probabilities of distress (PoDs) for individual banks. There are alternative approaches to estimating individual banks' probabilities of distress. For example, (i) the structural approach, (ii) credit default swaps, and (iii) out-of-the-money option prices (OOM). It is important to emphasize the fact that in the CIMDO framework, the PoDs for individual banks are exogenous variables and can therefore be calculated using any alternative for estimating PoDs. This makes estimating BSMD very flexible.

The CIMDO methodology is based on the minimum cross-entropy approach (Kullback, 1959). Under this approach, a posterior multivariate distribution p (the CIMDO density) is recovered using an optimization procedure, by which a prior density q is updated with empirical information, using a set of constraints. Thus, the posterior density satisfies the constraints imposed on the prior density. In this case, the banks' empirically estimated PoDs represent the information used to formulate the constraint set. Accordingly, the CIMDO density (the BSMD) is the posterior density that is closest to the prior distribution and that is consistent with the empirically estimated PoDs of banks in the system.

To formalize these ideas, we proceed by defining a banking system (portfolio of banks) composed of two banks, X and Y, whose logarithmic returns are characterized by the random variables x and y. Hence, we define the CIMDO objective function as:[4]

3. The PIT criterion for multivariate density's evaluation is presented in Diebold and others (1999).

4. A detailed definition and development of the CIMDO objective function and constraint set and the optimization procedure that is followed to solve the CIMDO function is presented in Segoviano (2006b).

$C(p,q)=\int\int p(x,y)\ln\left[\frac{p(x,y)}{q(x,y)}\right]dxdy$, where $q(x,y)$ and $p(x,y) \in \mathbb{R}^2$.

Note that the prior distribution follows a parametric form, q, consistent with economic intuition (for example, default is triggered by a drop in the firm's asset value below a threshold value) and with theoretical models (such as the structural approach to model risk). However, the parametric density, q, is usually inconsistent with the empirically observed measures of distress. Hence, the information provided by the empirical measures of distress of each bank in the system is of prime importance to estimating the posterior distribution. To incorporate this information into the posterior density, we formulate consistency-constraint equations that have to be fulfilled when optimizing the CIMDO objective function. These constraints are imposed on the marginal densities of the multivariate posterior density, and take the form:

$$\begin{aligned}&\int\int p(x,y)\,\chi\chi_{[x_d^x,\infty)}dxdy = PoD_t^x,\\&\int\int p(x,y)\,\chi_{[x_d^y,\infty)}dydx = PoD_t^y,\end{aligned} \tag{1}$$

where $p(x,y)$ is the *posterior* multivariate distribution that represents the unknown to be solved. PoD_t^x and PoD_t^y are the empirically estimated probabilities of distress (PoDs) for each bank in the system, and $\chi_{[x_d^x,\infty)}$, $\chi_{[x_d^y,\infty)}$ are indicating functions defined using distress thresholds x_d^x, x_d^y, estimated for each bank in the portfolio. To ensure that the solution for $p(x,y)$ represents a valid density, the conditions that $p(x,y) \geq 0$ and the probability additivity constraint, $\int\int p(x,y)dxdy=1$, must also be satisfied. Once the set of constraints is defined, the CIMDO density is recovered by minimizing the functional:

$$\begin{aligned}L(p,q) = &\int\int p(x,y)\ln p(x,y)dxdy - \int\int p(x,y)\ln q(x,y)\,dxdy\\&+\lambda_1\left[\int\int p(x,y)\,\chi_{[x_d^x,\infty)}dxdy - PoD_t^x\right]\\&+\lambda_2\left[\int\int p(x,y)\,\chi_{[x_d^y,\infty)}dydx - PoD_t^y\right]\\&+\mu\left[\int\int p(x,y)\,dxdy - 1\right],\end{aligned} \tag{2}$$

where λ_1, λ_2 represent the Lagrange multipliers of the consistency constraints and μ represents the Lagrange multiplier of the probability

additivity constraint. By using the calculus of variations, the optimization procedure can be performed. Hence, the optimal solution is represented by a *posterior* multivariate density taking the form:

$$\widehat{p(x,y)} = q(x,y)\exp\left\{-\left[1+\hat{\mu}+(\hat{\lambda}_1\chi_{[x_d^x,\infty)})+(\hat{\lambda}_2\chi_{[x_d^y,\infty)})\right]\right\}. \tag{3}$$

Intuitively, we know that imposing the constraint set on the objective function guarantees that the posterior multivariate distribution (BSMD) contains marginal densities that satisfy the PoDs observed empirically for each bank in the banking portfolio. Thus, in the modeling of portfolio risk, CIMDO-recovered distributions outperform the most commonly used parametric multivariate densities, according to the probability integral transformation (PIT) criterion.[5] This is because using the CIMDO approach to recover multivariate distributions, the available information, embedded in the constraint set, is used to adjust the shape of the multivariate density via the optimization procedure described above. This appears to be a more efficient manner of using the empirically observed information than under parametric approaches, which adjust the shape of parametric distributions via fixed sets of parameters. A detailed development of the PIT criterion and Monte Carlo studies used to evaluate specifications of the CIMDO density are presented in Segoviano (2006b).

1.3 The CIMDO copula: Distress Dependence among Institutions in the System

The BSMD reflects the structure of linear and nonlinear default dependence among banks included in the portfolio that is used to represent the banking system. This dependence structure is characterized by the copula function of the BSMD, that is, the CIMDO-copula, which changes at each period of time, consistent with shifts in the empirically observed PoDs. To illustrate this point, we heuristically introduce the copula approach to characterize dependence structures of random variables and explain the particular advantages of the CIMDO-copula. For further details see Segoviano (2008).

5. The standard and conditional normal distributions, the *t*-distribution, and the mixture of normal distributions.

1.3.1 The copula approach

The copula approach is based on the fact that any multivariate density, which characterizes the stochastic behavior of a group of random variables, can be broken into two subsets of information: (i) information about each random variable, that is, the marginal distribution of each variable; and (ii) information about the dependence structure among the random variables. Thus, to recover the latter, the copula approach sterilizes the marginal information for each variable, thereby isolating the dependence structure embedded in the multivariate density. Sterilization of marginal information is done by transforming the marginal distributions into uniform distributions; U(0,1), which are uninformative distributions.[6] For example, let x and y be two random variables with individual distributions $x \sim F$, $y \sim H$ and a joint distribution $(x,y) \sim G$. To transform x and y into two random variables with uniform distributions $\mathbf{U}(0,1)$ we define two new variables as $u=F(x)$, $v=H(y)$, both distributed as $\mathbf{U}(0,1)$ with joint density $c(u,v)$. Under the distribution of transformation of random variables, the copula function $c(u,v)$ is defined as:

$$c(u,v) = \frac{g\left[F^{(-1)}(u), H^{(-1)}(v)\right]}{f\left[F^{(-1)}(u)\right] h\left[H^{(-1)}(v)\right]}, \tag{4}$$

where g, f, and h are defined densities. From equation (4), we see that copula functions are multivariate distributions, whose marginal distributions are uniform on the interval [0,1]. Therefore, since each of the variables is individually (marginally) uniform, i.e. their information content has been sterilized, their joint distribution will only contain dependence information. Rewriting equation (4) in terms of x and y we get:

$$c\left[F(x), H(y)\right] = \frac{g(u,v)}{f(x)h(y)}. \tag{5}$$

Equation (5) tells us that the joint density of u and v is the ratio of the joint density of x and y to the product of the marginal densities. Thus, if the variables are independent, equation (5) is equal to one.

6. For further details, proofs and a comprehensive and didactical exposition of copula theory, see Nelsen (1999), and Embrechts, McNeil, and Straumann (1999) where properties and different types of copula functions are also presented.

The copula approach to model dependence possesses many positive features when compared to correlations. In comparison to correlation, the dependence structure characterized by copula functions, describes linear and nonlinear dependencies of any type of multivariate densities, throughout their entire domain. Moreover, copula functions are invariant under increasing and continuous transformations of marginal distributions. According to standard procedure, first, a given parametric copula is chosen and calibrated to describe the dependence structure among the random variables characterized by a multivariate density. Then, marginal distributions characterizing the individual behavior of random variables, are modeled separately. Lastly, marginal distributions are coupled with the chosen copula function to construct a multivariate distribution. Therefore, dependence modeling using standard parametric copulas involves two important shortcomings:

(i) It requires that modelers deal with the choice, proper specification and calibration of parametric copula functions, that is, the copula choice problem (CCP). In general, the CCP is a challenging task, since results are very sensitive to the functional form and parameter values of the chosen copula functions (Frey and McNeil, 2001). To specify the correct functional form and parameters, it is necessary to have information on the joint distribution of the variables of interest, in this case, joint distributions of distress, which are not available.

(ii) The parametric copula functions commonly employed in portfolio risk measurement require the specification of correlation parameters, which, as usually specified, remain fixed over time (see appendix A). Thus, although it is an improvement on dependence modeling using correlations, the dependence structure characterized using parametric copula functions, still poses the problem of characterizing dependence that remains fixed over time.[7]

1.3.2 The CIMDO copula

Our approach to model multivariate densities is the inverse of the standard copula approach. We first infer the CIMDO density as

7. Note that even if correlation parameters are dynamically updated using rolling windows, correlations remain fixed within these rolling windows. Moreover, most of the time, how the length of rolling windows is defined remains subjective.

explained in section 3.1. The CIMDO density portrays the dependence structure among the random variables that it characterizes. Thus, once we have inferred the CIMDO density, we can extract the copula function describing its dependence structure (the CIMDO copula). We do this by estimating marginal densities from the multivariate density and using Sklar's theorem (Sklar, 1959).

The CIMDO copula maintains all the benefits of the copula approach:

(i) It describes linear and nonlinear dependencies among the variables described by the CIMDO density. This dependence structure is invariant under increasing and continuous transformations of marginal distributions.

(ii) It characterizes the dependence structure along the entire domain of the CIMDO density. Nevertheless, the dependence structure characterized by the CIMDO copula appears to be more robust in the tail of the density (see discussion below), where our main interest lies (that is, to characterize distress dependence).

The CIMDO copula, however, avoids the drawbacks implicit in the use of standard parametric copulas:

(i) It circumvents the copula choice problem. The explicit choice and calibration of parametric copula functions is avoided because the CIMDO copula is extracted from the CIMDO density (as explained above). Thus, in contrast to most copula models, the CIMDO copula is recovered without explicitly imposing parametric forms that are difficult to model empirically and frequently wrongly specified, when using restricted data sets. Note that under such information constraints, when, for example, the only information available covers marginal probabilities of distress, the CIMDO copula is not only easily implementable, it outperforms the most common parametric copulas used in portfolio risk modeling under the PIT criterion. This is particularly true for the tail of the copula function, where distress dependence is characterized.

(ii) The CIMDO copula avoids the imposition of constant correlation parameter assumptions. It updates automatically when the probabilities of distress are used to infer the CIMDO density change. Therefore, the CIMDO copula incorporates banks' changing distress dependencies according to the dissimilar effects of shocks on individual banks' probabilities of distress, in a way that is consistent with the economic cycle.

To formalize these ideas, note that if the CIMDO density takes the form presented in equation (3), appendix B shows that the CIMDO copula, $c_c(u,v)$ is represented by

$$c_c(u,v) = \frac{1}{\int_{-\infty}^{+\infty} q\left[F_c^{-1}(u), y\right] \exp\left[-\hat{\lambda}_2 \chi_{x_d^y}(y)\right] dy} \times \frac{q\left[F_c^{-1}(u), H_c^{-1}(v)\right] \exp\left[-(1+\hat{\mu})\right]}{\int_{-\infty}^{+\infty} q\left[x, H_c^{-1}(v)\right] \exp\left[-\hat{\lambda}_1 \chi_{x_d^x}(x)\right] dx}, \tag{6}$$

where $u=F_c(x) \Leftrightarrow x=F_c^{-1}(u)$, and $v=H_c(y) \Leftrightarrow y=H_c^{-1}(v)$.

Equation (6) shows that the CIMDO copula is a nonlinear function of $\hat{\lambda}_1$, $\hat{\lambda}_2$ and $\hat{\mu}$, the Lagrange multipliers of the CIMDO functional presented in equation (2). As with all optimization problems, the Lagrange multipliers reflect the change in the objective function's value, as a result of a marginal change in the constraint set. Therefore, as the empirical PoDs of individual banks change at each period of time, the Lagrange multipliers change, the values of the constraint set change, and the CIMDO copula changes. Consequently, the default dependence among system banks changes.

As mentioned, then, the default dependence gets updated automatically with changes in empirical PoDs for each period in time. This is a relevant improvement over most risk models, which usually account for linear dependence (correlation) only, which, moreover is also assumed to remain constant throughout the cycle or over a fixed period of time.

2. Banking Stability Measures

The BSMD characterizes the probability of distress of the individual banks included in the portfolio, their distress dependence, and changes across the economic cycle. This is a rich set of information that allows us to analyze (define) banking stability from three different, yet complementary, perspectives. For this purpose, we define a set of BSMs to quantify:

(i) Tail risk, defined as common distress of the financial institutions in a system;

(ii) Distress among specific institutions;
(iii) Cascade effects, defined as distress in the system associated with distress in a specific institution.

We hope that the complementary perspectives on financial stability offered by the BSMs proposed here constitute a useful tool set to help financial supervisors identify how risks are evolving and where contagion could most easily develop. To illustrate and make it easier to present definitions below, we proceed by defining a banking system (portfolio of banks) consisting of three banks whose asset values are characterized by the random variables x, y and r. We then use the procedure described in section 3.1 to infer the CIMDO density function, which takes the form:

$$\widehat{p(x,y,r)} = q(x,y,r)\exp\left\{-\begin{bmatrix} 1+\hat{\mu}+(\hat{\lambda}_1\chi_{[x_d^x,\infty)}) \\ +(\hat{\lambda}_2\,\chi_{[x_d^y,\infty)})+(\hat{\lambda}_3\,\chi_{[x_d^r,\infty)}) \end{bmatrix}\right\}, \tag{7}$$

where $q(x,y,r)$ and $p(x,y,r) \in \mathbb{R}^3$.

2.1 Perspective 1: Tail Risk

To analyze common distress in the banks comprising the system, we propose the joint probability of distress (JPoD) and the banking stability index.

2.1.1 The joint probability of distress

The joint probability of distress represents the probability of all banks in the system (portfolio) becoming distressed, that is, the tail risk of the system. The JPoD reflects changes in individual bank PoDs and captures changes in distress dependence among the banks. The latter increases in times of financial distress. Therefore, in such periods, the banking system's JPoD may experience larger and nonlinear increases than those experienced by the (average) PoDs of individual banks. For the hypothetical banking system defined in equation (7) the JPoD is defined as $P(X \cap Y \cap R)$ and is estimated by integrating the density (BSMD) as follows:

$$\int_{x_d^r}^{\infty}\int_{x_d^y}^{\infty}\int_{x_d^x}^{\infty} \widehat{p(x,y,r)}\,dxdydr = JPoD. \tag{8}$$

2.1.2 The banking stability index

The banking stability index (BSI) is based on the conditional expectation of default probability measure, developed by Huang (1992).[8] The BSI reflects the expected number of banks becoming distressed, given that at least one bank has become distressed. A higher number signifies increased instability. For example, for a system of two banks, the BSI is defined as follows:

$$\text{BSI} = \frac{P(X \geq x_d^x) + P(Y \geq x_d^y)}{1 - P(X < x_d^x, Y < x_d^y)}. \tag{9}$$

The BSI represents a probability measure based on the condition of any bank, without indicating the specific bank, becoming distressed.[9]

2.2 Perspective 2: Distress Between Specific Banks

2.2.1 Distress dependence matrix

For each period under analysis and for each pair of banks in the portfolio, we estimate the set of pairwise conditional probabilities of distress, presented in the distress dependence matrix (DiDe). This matrix contains the probability of distress of the bank specified in the row, if the bank specified in the column becomes distressed. Although conditional probabilities do not imply causation, this set of pairwise conditional probabilities can provide important insights into interlinkages and the likelihood of contagion between banks in the system. Table 1 provides the DiDE for the hypothetical banking system defined in equation (7), on a given date.

Table 1. Distress Dependence Matrix

	Bank X	*Bank Y*	*Bank R*
Bank X	1	P(X|Y)	P(X|R)
Bank Y	P(Y|X)	1	P(Y|R)
Bank R	P(R|X)	P(R|Y)	1

Source: Segoviano and Goodhart (2009).

8. This function is presented in Huang (1992). For empirical applications, see Hartmann and others (2001).

9. Huang (1992) shows that this measure can also be interpreted as a relative measure of banking linkage. When the BSI=1 in the limit, banking linkage is weak (asymptotic independence). As the value of the BSI increases, banking linkage increases (asymptotic dependence).

Here, for example, the probability of distress in bank X conditional on bank Y becoming distressed is estimated by

$$P(X \geq x_d^x \big| Y \geq x_d^y) = \frac{P(X \geq x_d^x, Y \geq x_d^y)}{P(Y \geq x_d^y)}. \tag{10}$$

2.3 Perspective 3: Cascade Effects

2.3.1 The probability of cascade effects (PCE)

This indicator characterizes the likelihood that one, two, or more institutions, up to the total number of Financial Institutions (FIs hereafter) in the system become distressed given that a specific FI becomes distressed. Therefore, this measure quantifies the potential cascade effects in the system, given distress occurring in a specific bank. Consequently, we propose this measure as an indicator to quantify the systemic importance of a specific bank if it becomes distressed. Again, note that conditional probabilities do not imply causation. We do consider, however, that the PCE can provide important insights into systemic interlinkages among the banks in a system. For example, in a system with four banks, X, Y, Z, and R, the PCE can be defined as follows:

$$\begin{aligned} PCE = \; & P(Y|X) + P(Z|X) + P(R|X) \\ & -\left[P(Y \cap R|X) + P(Y \cap Z|X) + P(Z \cap R|X)\right] \\ & +P(Y \cap R \cap Z|X). \end{aligned} \tag{11}$$

3. Banking Stability Measures: Empirical Results

We have used the BSM proposed by Segoviano and Goodhart (2009) to examine relative changes in stability over time in the following cases:

(i) Financial stability and spillovers among country/regions;
(ii) Spillovers between foreign banks (from developed countries) and emerging sovereign markets;
(iii) Spillovers between developed country banks and developed sovereign markets;
(iv) Spillovers between the banking system and corporate sectors.

Our estimations are performed from 2005 to February 2009, using publicly available data, and include major American and European banks, and sovereign banks in Latin America, Eastern Europe, Europe, and Asia. The flexibility inherent in our approach is relevant to monitoring bank stability, since cross-border financial linkages are growing and becoming increasingly significant, as has been underlined by turmoil in financial markets in recent months. Thus, monitoring banking stability cannot stop at national borders.

3.1 Estimating the Probability of Individual Bank Distress

The proposed BSMs can be constructed from a very limited set of data, such as empirical measures of distress for individual banks, which we have labeled probabilities of distress (PoDs). These measures can be estimated using alternative approaches, such as Merton-type models, credit default swaps (CDS), option prices, and bond spreads, depending on the data available. This means that the data set necessary to estimate BSMs is available in most countries. Consequently, such measures can be developed for a wide range of developing and developed countries.

Being able to establish this kind of set of measures with minimal base components, makes a broader range of comparative analysis, including both time series and cross-sections, possible. In the applications below, we used CDS-PoDs, since they seemed the best available distress indicator for the banks under analysis. Note, however, that estimating the proposed BSMs is not intrinsically related to CDS-PoDs. Thus, if we were to find a better approach, replacing the PoD approach selected here to estimate BSMs would be straightforward, since in this framework PoDs are exogenous variables.[10]

10. Arguments against using CDS-PoDs emphasize that CDS spreads may sometimes overshoot. They do not generally stay wrong for long, however. Rating agencies have mentioned that CDS spreads frequently anticipate rating changes. Although the magnitude of shifts may sometimes be unrealistic, the direction is usually a good distress signal. For these reasons, and due to the problems encountered with other approaches (which we consider more serious), we decided to use CDS-PoDs to estimate the proposed BSMs.

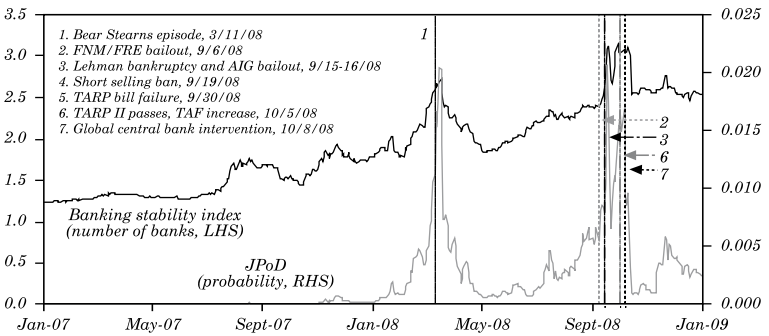
3.2 Financial Stability and Spillovers among regions[11]

To analyze financial stability across regions, we included major American, European, and Asian banks, grouped in alternative portfolios, to observe:

3.2.1 Perspective 1: Tail risk

- **FIs are highly interconnected, with distress in one FI associated with high probability of distress elsewhere.** This is clearly indicated by the JPoD and the BSI. Moreover, movements in the JPoD and BSI coincide with events considered relevant by markets on specific dates (figure 3). Note also that risks vary by geographical location and business area of the FI (figure 4).

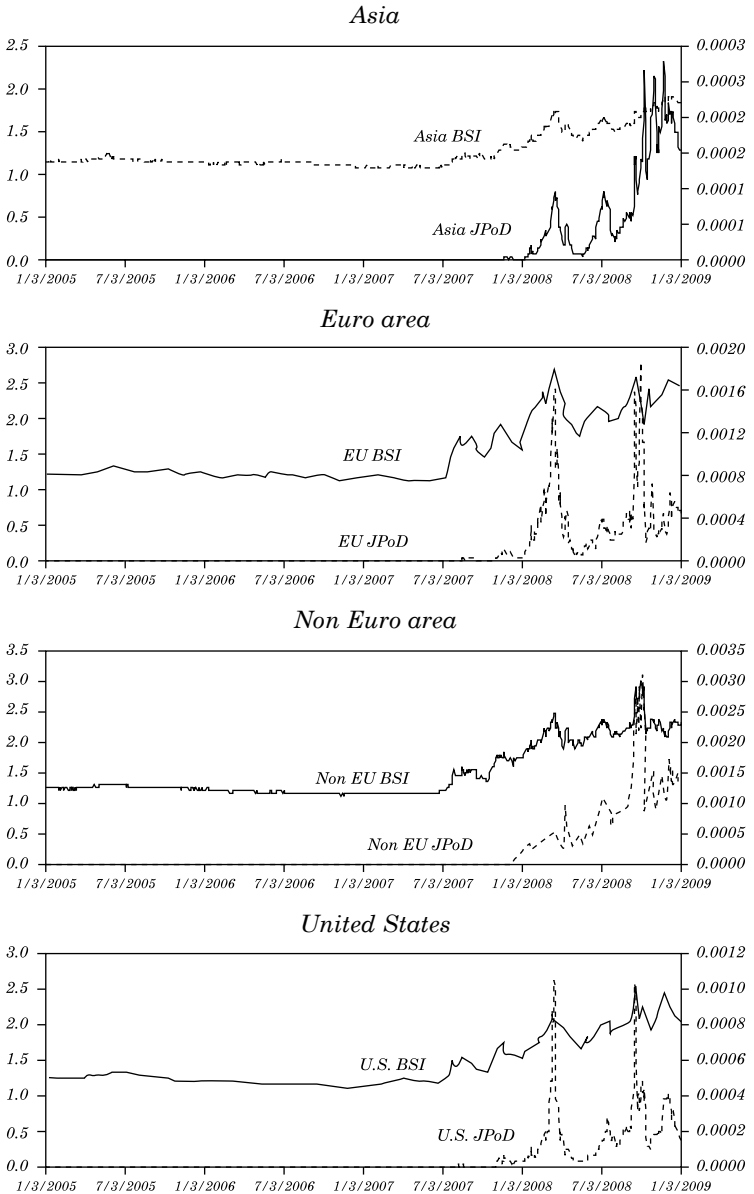
Figure 3. Tail Risk: January 2007-February 2009



Sources: Bloomberg L.P.; IMF staff estimates.
Note: Global group consists of Bank of America, Citigroup, J.P. Morgan Chase & Co., Wachovia, Goldman Sachs, Lehman Brothers, Merrill Lynch, Morgan Stanley, Deutsche Bank, Royal Bank of Scotland, UBS, HSBC, PMI, AMBAC Financial, AIG, and Swiss Re.

11. The authors would like to thank Tami Bayoumi for insightful discussions and contributions to the analysis of these empirical results.

Figure 4. Tail Risk by Regions: January 2007-February 2009
(BSI: number of banks, LHS; JPoD: probability, RHS)



Source: Authors' calculations.

3.2.2 Perspective 2: Distress between specific institutions

Table 2 illustrates the following:

- **Distress dependence across major American FIs has greatly increased.** This is clearly shown by the conditional PoDs presented in the DiDe. On average, if any of the U.S. FIs fell into distress, the average probability of this affecting other FIs increased from 23 percent on 1 July 2007 to 41 percent on 12 September 2008.
- **By September, Lehman and AIG vulnerability had increased significantly.** This is revealed by Lehman's and AIG's large PoDs conditional on any other FI experiencing distress, which increased from 30 and 15 percent, respectively, on 1 July 2007 to 52 and 44 percent on 15 August, and 56 and 55 percent, on average, on 12 September 2008 (row-average Lehman and AIG). Moreover, a Lehman default was estimated on 12 September to raise the chances of distress elsewhere by 46 percent In other words, the PoD of any other bank conditional on Lehman experiencing distress went from 25 percent on 1 July 2007 to 37 percent on 12 September 2008 (column-average Lehman).

Note that a similar effect in the system would have been caused by the distress of AIG, since the PoD of any other bank dependent on AIG experiencing distress went from 20 percent on 1 July 2007 to 34 percent on 12 September 2008 (column-average AIG).

- **Lehman's connections to the other major U.S. banks were similar to AIG's.** This can be seen by comparing the chances of each one of the U.S. banks being affected by distress in Lehman and AIG (column Lehman versus column AIG) on 12 September. Links were particularly close between Lehman, AIG, Washington Mutual, and Wachovia, all of which were particularly exposed to housing. On 12 September, a Lehman bankruptcy implied an 88, 43, and 27 percent likelihood that Washington Mutual, AIG, and Wachovia, respectively, would fall into distress.
- **Distress dependence appears to be an early warning sign.** It is also very interesting to note that up to a month earlier than the Lehman event, distress dependence was already signaling that a default of Lehman or AIG would have caused significant disruptions in the system. This is revealed by the PoD for any other bank dependent on Lehman or AIG experiencing distress, which increased significantly to 41 and 39 percent, respectively,

Table 2. Distress Dependence Matrix

1 July 2007	*Citi*	*BAC*	*JPM*	*Wacho.*	*WaMu*	*GS*	*LB*	*ML*	*MS*	*AIG*	*Row average*
Citibank	1.00	0.09	0.08	0.08	0.05	0.06	0.06	0.06	0.06	0.05	0.16
Bank of America	0.08	1.00	0.22	0.21	0.08	0.08	0.07	0.09	0.09	0.11	0.20
J.P. Morgan Chase	0.10	0.33	1.00	0.23	0.09	0.14	0.12	0.14	0.12	0.11	0.24
Wachovia Bank	0.08	0.27	0.2	1.00	0.08	0.08	0.07	0.08	0.08	0.10	0.20
Washington Mutual	0.14	0.25	0.18	0.20	1.00	0.10	0.10	0.13	0.11	0.12	0.23
Goldman Sachs	0.13	0.20	0.23	0.16	0.08	1.00	0.27	0.23	0.26	0.13	0.27
Lehman Brothers	0.16	0.24	0.25	0.19	0.11	0.35	1.00	0.29	0.26	0.14	0.30
Merrill Lynch	0.15	0.26	0.27	0.19	0.13	0.28	0.26	1.00	0.26	0.15	0.30
Morgan Stanley	0.15	0.25	0.23	0.19	0.10	0.30	0.23	0.25	1.00	0.12	0.28
AIG	0.05	0.11	0.07	0.08	0.04	0.05	0.04	0.05	0.04	1.00	0.15
Column average	0.20	0.30	0.27	0.25	0.17	0.24	0.22	0.23	0.23	0.20	0.23
15 August 2008											
Citibank	1.00	0.32	0.32	0.23	0.13	0.28	0.23	0.23	0.25	0.21	0.32
Bank of America	0.20	1.00	0.41	0.24	0.09	0.24	0.17	0.19	0.21	0.19	0.30
J.P. Morgan Chase	0.18	0.37	1.00	0.20	0.07	0.25	0.17	0.18	0.20	0.15	0.28
Wachovia Bank	0.41	0.69	0.65	1.00	0.23	0.45	0.37	0.39	0.41	0.39	0.5
Washington Mutual	0.83	0.92	0.89	0.85	1.00	0.80	0.77	0.82	0.80	0.78	0.85
Goldman Sachs	0.21	0.28	0.34	0.19	0.09	1.00	0.28	0.26	0.32	0.18	0.31
Lehman Brothers	0.42	0.51	0.56	0.39	0.22	0.69	1.00	0.52	0.54	0.36	0.52
Merrill Lynch	0.39	0.52	0.58	0.37	0.21	0.61	0.48	1.00	0.53	0.36	0.50
Morgan Stanley	0.31	0.41	0.44	0.28	0.15	0.52	0.35	0.37	1.00	0.24	0.41
AIG	0.36	0.52	0.48	0.38	0.20	0.41	0.32	0.35	0.34	1.00	0.44
Column average	0.43	0.55	0.57	0.41	0.24	0.53	0.41	0.43	0.46	0.39	0.44

Table 2. (continued)

12 September 2008	*Citi*	*BAC*	*JPM*	*Wacho.*	*WaMu*	*GS*	*LB*	*ML*	*MS*	*AIG*	*Row average*
Citibank	1.00	0.20	0.19	0.14	0.07	0.17	0.13	0.14	0.16	0.11	0.23
Bank of America	0.14	1.00	0.31	0.18	0.05	0.16	0.10	0.13	0.15	0.11	0.23
J.P. Morgan Chase	0.13	0.29	1.00	0.16	0.05	0.19	0.11	0.14	0.16	0.09	0.23
Wachovia Bank	0.34	0.60	0.55	1.00	0.17	0.36	0.27	0.31	0.34	0.29	0.42
Washington Mutual	0.93	0.97	0.95	0.94	1.00	0.91	0.88	0.92	0.91	0.89	0.93
Goldman Sachs	0.15	0.19	0.24	0.13	0.06	1.00	0.18	0.20	0.27	0.11	0.25
Lehman Brothers	0.47	0.53	0.58	0.43	0.25	0.75	1.00	0.59	0.62	0.37	0.56
Merrill Lynch	0.32	0.41	0.47	0.30	0.16	0.53	0.37	1.00	0.48	0.26	0.43
Morgan Stanley	0.21	0.28	0.29	0.19	0.09	0.40	0.22	0.27	1.00	0.14	0.31
AIG	0.50	0.66	0.59	0.53	0.29	0.54	0.43	0.49	0.47	1.00	0.55
Column average	0.42	0.51	0.52	0.40	0.22	0.50	0.37	0.42	0.46	0.34	0.41

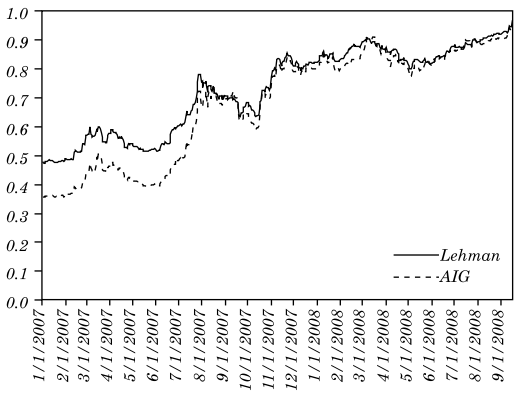
Source: Authors' calculations.

on 15 August 2008 (column-average Lehman and AIG). Moreover, On 15 August, a Lehman bankruptcy implied a 77, 32, and 37 percent likelihood that Washington Mutual, AIG, and Wachovia, respectively, would experience distress. The Lehman bankruptcy seems to have sealed the fate of AIG and Washington Mutual, while boosting the pressure on Wachovia, as indicated by the DiDe. Even though distress dependence does not imply causation, these results show that the analysis of distress dependence, even several weeks prior to a distress event, can provide useful insights of how distress in a specific institution can affect other institutions and ultimately the stability of the system.

3.2.3 Perspective 3: Cascade effects

- **The probability of cascade effects (PCE) signaled major impacts on markets if Lehman or AIG became distressed.** The PCE for these institutions reached 97 and 95 percent, respectively, on 12 September 2008. Thus, the PCE also signaled the possible domino effect, observed in the days after Lehman's collapse (figure 5). Note that the PCE for both institutions had already increased by August 2008. This analysis is in line with the insights brought by the DiDe in perspective 2, which indicated Lehman's distress would be associated with distress in several institutions.

Figure 5. Probability of Cascade Effects if Lehman/AIG fall into Distress



Source: Authors' calculations.

3.3 Spillovers Between Foreign Banks and Emerging Sovereign Markets

In this section, we extend our methodology to analyze how rising problems in advanced country banking systems are linked with increasing risks in emerging markets. For this purpose, we use CDS spreads based on sovereign and bank bonds to derive probabilities of sovereign and bank distress. These PoDs, then, represent markets' views on the risk of distress for these banks and countries. While absolute risks are discussed, the focus is largely on cross distress dependence of risks and what this can tell us about emerging vulnerabilities (perspective 2). Specifically, using publicly available data we estimate cross vulnerabilities between Latin American, Eastern European, and Asian emerging markets and the advanced country banks with the most presence in these regions. Countries and banks analyzed are:

- **Latin America**. Countries: Mexico, Colombia, Brazil and Chile. Banks: BBVA, Santander, Citigroup, and HSBC.
- **Eastern Europe**. Countries: Bulgaria, Croatia, Hungary and Slovakia. Banks: Intesa, Unicredito, Erste, Société Générale, and Citigroup.
- **Asia**. Countries: China, South Korea, Thailand, Malaysia, the Philippines, and Indonesia. Banks: Citigroup, J.P. Morgan Chase, HSBC, Standard and Chartered, BNP, Deutsche Bank, and DBS.

The key observation from this analysis is that concerns about bank solvency and emerging market instability appear to be highly interlinked. To illustrate these interlinkages, we present distress dependence matrices estimated for each region in table 3.[12] To analyze how distress dependence has evolved over time, we also estimate the time series of the conditional probabilities of distress of banks/countries if other banks/countries default.[13]

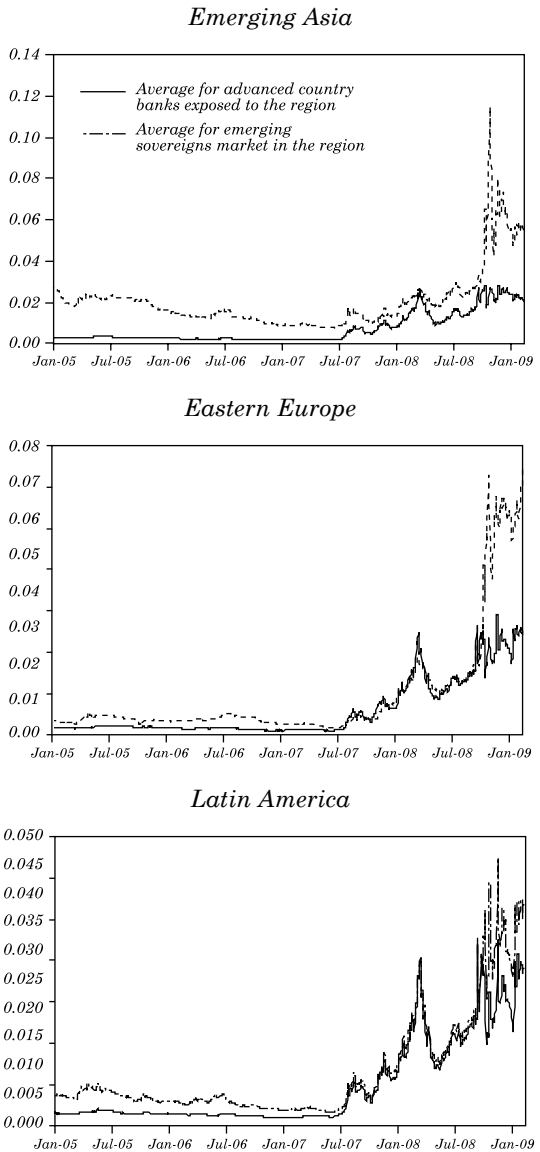
12. These matrices can be estimated for each day. They report links across countries (bottom right, quadrant 4), and across banks (top left, quadrant 1). The bottom left (quadrant 3) reports how sovereign distress is conditional on bank problems, while the top right (quadrant 2) indicates the opposite.

13. Note that there is a daily time series for each of the quadrants described in the previous footnote. Each observation in the time series corresponds to the average of the conditional probabilities in each quadrant, at each day.

3.3.1 Distress between foreign banks and emerging sovereign markets

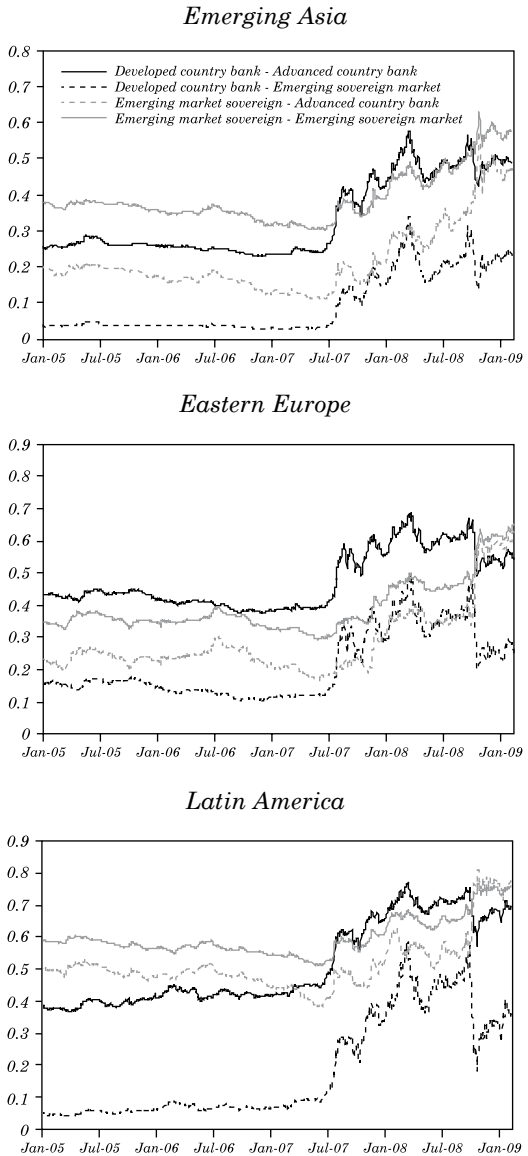
- **The analysis shows that risk in sovereign markets and banks increased markedly after October 2008.** In the run-up to the crisis, there was little concern about risks to sovereigns and parent banks in Eastern Europe, and risk perceptions in Latin America and Asia were falling. From July 2007 to September 2008, both sovereign risk and bank risk increased and moved in tandem, but from October 2008, risk in sovereigns has been significantly higher than in banks (figure 6). This may reflect the deepening downturn in emerging economies in late 2008 and the support received by banks in developed countries from their sovereigns.
- **Bank problems appear to have a significant impact on sovereign distress.** This is seen by comparing the probability of distress of the emerging sovereign Markets conditional on distress in the mature market banks in July 2007 and in September 2008. In the last quarter of 2008, sovereign risk conditional on bank risk has increased further (figure 7).
- **Bank location is important to sovereign distress.** Quadrant 3 of the distress dependence matrices (table 3) reveals that distress among Spanish banks is associated with the most distress in Latin America, while distress among Italian banks has the most impact on Eastern Europe. Distress of standard chartered banks is associated with significant stress in Asia (quadrant 3, column-average). These results suggest that location matters, since these banks have a substantial presence in the respective regions under analysis.
- **Direct links between banks and countries matter.** Distress in countries with a particularly large foreign bank presence, such as Mexico and the Czech Republic, is most strongly associated with potential banking distress (quadrant 2). Direct links between individual banks and countries also matter, for example, distress at Citigroup, Intesa, and DBS were more important to Mexico, Hungary, and Indonesia than other countries (quadrant 3).
- **The results also illustrate the influence of systemic risk, which constitutes an indirect link to Asia, over and above direct regional and bilateral links.** Direct ownership and lending by foreign banks is generally lower

Figure 6. Probabilities of Distress



Source: Authors' calculations.

Figure 7. Distress Dependence over Time
(average conditional probabilities for the region)



Source: Authors' calculations.

in Asia than in Eastern Europe or Latin America, insulating banking systems somewhat from these direct links, and increasing the relative importance of indirect links involving bank and/or sovereign distress. In addition, links between banks may be somewhat less important for emerging Asia, as borrowing through debt markets tends to play a larger role in local financial systems. Indirect effects are particularly evident in South Korea and Indonesia. An important strength of our approach is that market prices reflect the perception that direct and indirect links exist. For the former, market presence might be an important element, as in Latin America and Eastern Europe. For the latter, however, liquidity pressures and systemic banking distress/macroeconomic spillovers might play an important role. This feature of our approach appears to be particularly relevant in Asia.

- **Overall, the results indicate that systemic bank risks and emerging market vulnerabilities appear to be highly dependent.** This probably reflects the fact that distress in individual banks acts as a bellwether for the state of the financial system overall, through direct or indirect links.

Table 3. Distress Dependence Matrices: Sovereign Markets: and Banks
(as of February 2009)

Latin America					
	BBVA	*Santander*	*Citigroup*	*HSBC*	*Row average*
BBVA	1.000000	0.725706	0.326296	0.637743	0.672436
Santander	0.728609	1.000000	0.315021	0.627339	0.667742
Citigroup	0.751264	0.722414	1.000000	0.776343	0.812505
HSBC	0.586723	0.574852	0.310214	1.000000	0.617947
Column average	0.766649	0.755743	0.487883	0.760356	0.692658
Mexico	0.865202	0.863165	0.809673	0.874189	0.853057
Colombia	0.823127	0.815681	0.646378	0.817612	0.775700
Brazil	0.821372	0.817196	0.700703	0.820338	0.789902
Chile	0.738229	0.730452	0.564896	0.742177	0.693939
Column average	0.811983	0.806623	0.680412	0.813579	0.778149
	Mexico	*Colombia*	*Brazil*	*Chile*	*Row average*
BBVA	0.275122	0.256586	0.275776	0.361877	0.292340
Santander	0.275571	0.255282	0.275471	0.359497	0.291455
Citigroup	0.592785	0.463909	0.541666	0.637557	0.558979
HSBC	0.255741	0.234477	0.253395	0.334707	0.269580
Column average	0.349805	0.302564	0.336577	0.423410	0.353089
Mexico	1.000000	0.651145	0.803716	0.872234	0.831774
Colombia	0.664230	1.000000	0.660733	0.754643	0.769902
Brazil	0.761189	0.613444	1.000000	0.800777	0.793853
Chile	0.565809	0.479885	0.548478	1.000000	0.648543
Column average	0.747807	0.686119	0.753232	0.856914	0.761018

Table 3. (continued)

Eastern Europe						
	Intesa	*Unicredito*	*Erste*	*Société*	*Citigroup*	*Row average*
Intesa	1.000000	0.475783	0.301497	0.450473	0.210372	0.487625
Unicredito	0.599617	1.000000	0.365881	0.550721	0.266108	0.556465
Erste	0.557821	0.537140	1.000000	0.574143	0.338382	0.601497
Société Générale	0.384907	0.373383	0.265153	1.000000	0.183779	0.441444
Citigroup	0.518365	0.520285	0.450654	0.529977	1.000000	0.603856
Column average	0.612142	0.581318	0.476637	0.621063	0.399728	0.538178
Bulgaria	0.708755	0.718608	0.715218	0.738093	0.632545	0.702644
Croatia	0.804806	0.793321	0.756003	0.773592	0.663734	0.758291
Hungary	0.831557	0.81284	0.810723	0.784304	0.664342	0.780753
Slovakia	0.352204	0.357517	0.300776	0.351336	0.327638	0.337894
Estonia	0.687141	0.672014	0.637246	0.635676	0.559833	0.638382
Czech Republic	0.610193	0.625443	0.638816	0.593791	0.449097	0.583468
Column average	0.665776	0.6632905	0.64313033	0.646132	0.5495315	0.633572

	Bulgaria	*Croatia*	*Hungary*	*Slovakia*	*Estonia*	*Czech Rep.*	*Row average*
Intesa	0.139906	0.177797	0.192069	0.176178	0.166857	0.242417	0.182537
Unicredito	0.178771	0.220875	0.236603	0.225381	0.205656	0.313147	0.230072
Erste	0.261211	0.309007	0.346445	0.278363	0.286297	0.469552	0.325146
Société Générale	0.124492	0.146027	0.154783	0.150164	0.131893	0.201566	0.151488
Citigroup	0.307667	0.361306	0.378085	0.403829	0.334969	0.439626	0.370914
Column average	0.202409	0.243002	0.261597	0.246783	0.225134	0.333262	0.252031
Bulgaria	1.000000	0.707068	0.668112	0.758508	0.710653	0.777554	0.770316
Croatia	0.631785	1.000000	0.678201	0.703084	0.860053	0.820782	0.782318
Hungary	0.571006	0.648697	1.000000	0.650592	0.640253	0.852863	0.727235
Slovakia	0.299327	0.310517	0.300402	1.000000	0.314773	0.396426	0.436908
Estonia	0.577698	0.628698	0.608991	0.648420	1.000000	0.731451	0.699210
Czech Republic	0.386346	0.456421	0.498531	0.499141	0.447083	1.000000	0.547920
Column average	0.493232	0.608867	0.617225	0.700247	0.652432	0.760304	0.638718

Table 3. (continued)

Asia								
	HSBC	*SC*	*Citigroup*	*Deutche*	*BNP*	*DBS*	*JPM*	*Row average*
HSBC	1.000000	0.400728	0.240106	0.467571	0.594485	0.243707	0.277133	0.460533
Standard and Chartered	0.731765	1.000000	0.373773	0.653803	0.785633	0.399322	0.422132	0.623775
Citigroup	0.600891	0.512247	1.000000	0.680894	0.650505	0.358004	0.847451	0.664285
Deutsche Bank	0.390320	0.298881	0.227122	1.000000	0.570166	0.182848	0.299087	0.424061
BNP	0.349454	0.252899	0.152794	0.401492	1.000000	0.154917	0.194071	0.357947
DBS	0.476818	0.427845	0.279885	0.428549	0.515625	1.000000	0.296335	0.489294
J.P. Morgan Chase	0.274964	0.229358	0.335977	0.355477	0.327567	0.150275	1.000000	0.381945
Column average	0.546316	0.445994	0.372808	0.569684	0.634854	0.355582	0.476601	0.485977
South Korea	0.594517	0.587287	0.398186	0.547021	0.616806	0.709589	0.402420	0.550832
Malaysia	0.419980	0.438035	0.305322	0.447027	0.503945	0.548694	0.312387	0.425056
Thailand	0.410019	0.407681	0.275756	0.374748	0.441744	0.478346	0.280762	0.381294
China	0.413471	0.368967	0.273494	0.363895	0.412435	0.376860	0.295244	0.357767
Philippines	0.472991	0.510020	0.358525	0.493129	0.527604	0.547252	0.334387	0.463415
Indonesia	0.681152	0.693283	0.522499	0.630787	0.690313	0.825260	0.513146	0.650920
Column average	0.498688	0.500879	0.355630	0.476101	0.532141	0.581000	0.356391	0.471547

Table 3. (continued)

	S. Korea	*Malaysia*	*Thailand*	*China*	*Philippines*	*Indonesia*	*Row average*
HSBC	0.200850	0.199495	0.193485	0.218316	0.135680	0.129475	0.179550
Standard and Chartered	0.362310	0.379956	0.351305	0.355753	0.267159	0.240644	0.326188
Citigroup	0.336656	0.362956	0.325657	0.361394	0.258380	0.248554	0.315433
Deutsche Bank	0.154272	0.177260	0.147623	0.160394	0.118085	0.100092	0.142954
BNP	0.122491	0.140713	0.122536	0.128010	0.088965	0.077133	0.113308
DBS	0.469029	0.509939	0.441641	0.389318	0.307138	0.306915	0.403997
J.P. Morgan Chase	0.134889	0.147226	0.131452	0.154671	0.095170	0.096777	0.126697
Column average	0.254357	0.273935	0.244814	0.252551	0.181368	0.171370	0.229732
South Korea	1.000000	0.686822	0.605330	0.614034	0.484226	0.438772	0.638198
Malaysia	0.488483	1.000000	0.460463	0.463792	0.380784	0.334829	0.521392
Thailand	0.433370	0.463506	1.000000	0.377362	0.290046	0.299040	0.477221
China	0.392881	0.417240	0.337257	1.000000	0.275819	0.253024	0.446037
Philippines	0.570289	0.630551	0.477141	0.507694	1.000000	0.415918	0.600265
Indonesia	0.779839	0.836727	0.742386	0.702845	0.627663	1.000000	0.781577
Column average	0.610810	0.672474	0.603763	0.610955	0.509756	0.456931	0.577448

Source: IMF staff estimates.

3.4 Spillovers between Developed Country Banks and their Sovereign Markets

This section applies the proposed model to study the transmission of shocks from banks in developed countries (with large exposure to emerging market, such as Austria, the United Kingdom, France, and Germany) to their own sovereign markets.

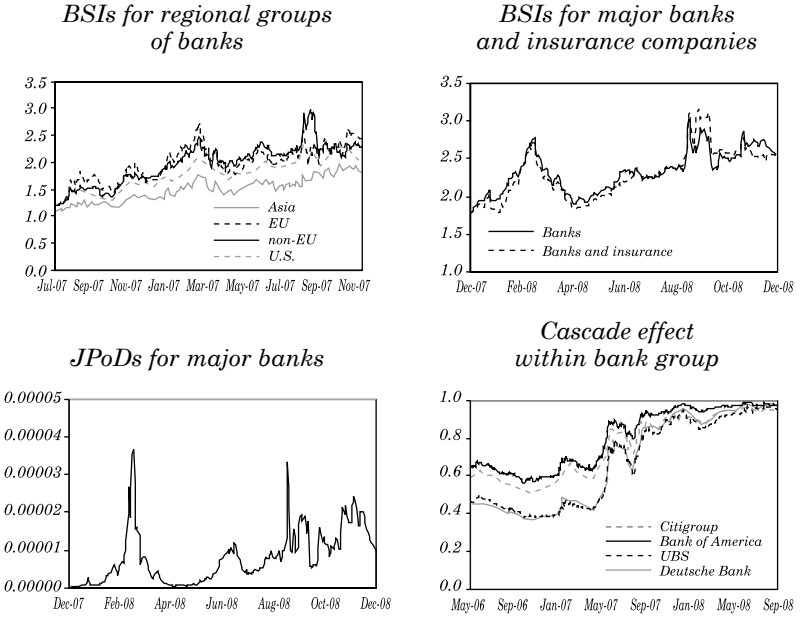
3.4.1 Tail risk and cascade effects

- **Measures of bank interconnectedness started to rise at the onset of the crisis**. The joint probability of distress (JPoD) and banking stability index indicate that systemic tail risk has risen substantially (figure 8).
- **The probability of cascade effects has also increased substantially,** suggesting that future shocks would be transmitted quickly through the financial system (figure 8).

3.4.2 Distress between banks and sovereign markets in developed economies

- **Links between advanced country banks and sovereign markets increased markedly after October**. As the fiscal costs of potential bank bailouts have become apparent, banking sector concerns and sovereign risk have become increasingly intertwined. This is significant in Austria and the United Kingdom (figure 9).

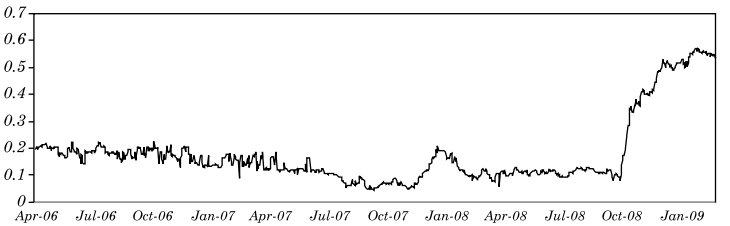
Figure 8. Tail Risk and Cascade Effects



Source: IMF staff estimates.

Figure 9. Distress between Banks and Sovereign Markets in Developed Economies

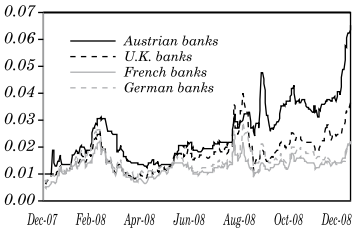
Probability of distress of an advanced country sovereign market, conditional on an advanced country bank falling into distress (sample average)



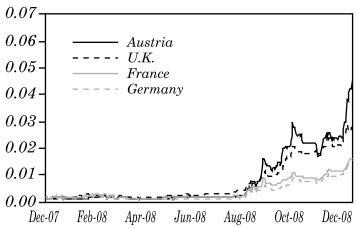
Source: IMF staff estimates.

Figure 9. (continued)

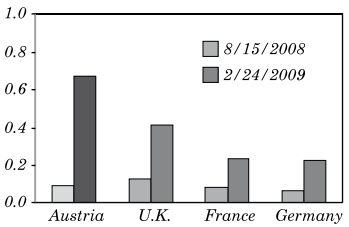
Banks' average probability of distress



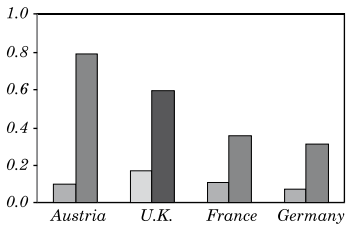
Sovereign market probability of distress



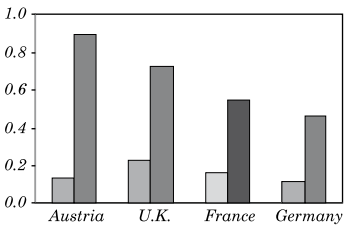
Probability of sovereign market distress conditional on distress of Austrian banks



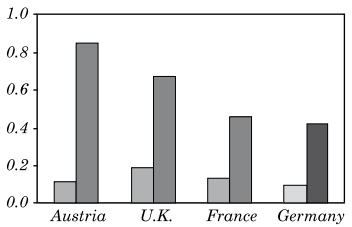
Probability of sovereign market distress conditional on the distress of U.K. banks



Probability of sovereign market distress conditional on distress of the French banks



Probability of sovereign market distress conditional on the distress of German banks



Sources: Bloomberg and IMF staff estimates.

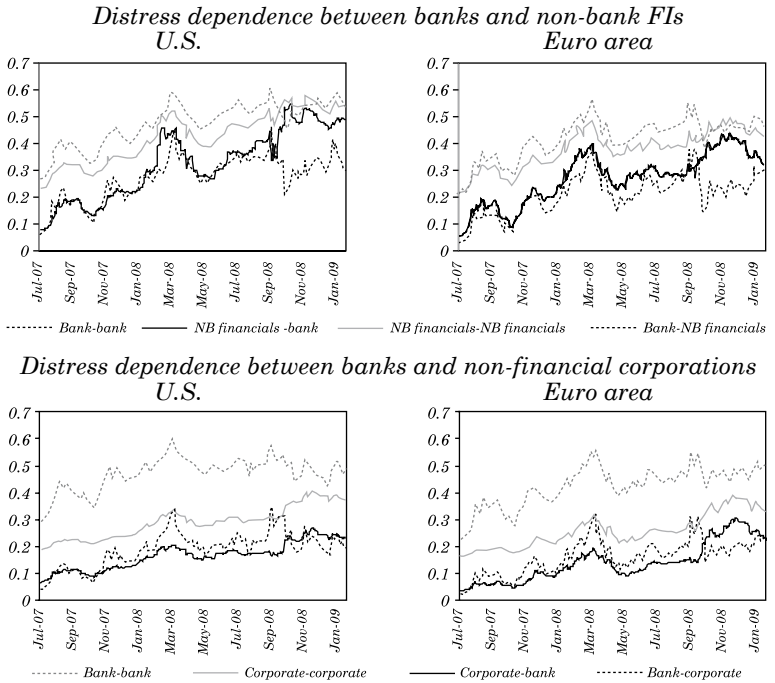
3.5 Spillovers between the Banking System and Corporate Sectors

To analyze spillovers between the banking system and the corporate sector, we estimated linkages between non-bank financial companies, other corporations and banks in the U.S. and Europe.

3.5.1 Distress between banks and corporations

- **Banks in developed countries have gradually become more interlinked with non-banks and non-financial corporations**. Banks became less dependent on other corporations in late 2008 (likely due to public support), but spillovers to other corporations continued to rise (figure 10). This constitutes evidence of spillovers from the banking crisis into the real economy.

Figure 10. Distress between Banks and Corporations in Developed Economies



Source: IMF staff estimates.

4. Conclusions

The purpose of this paper is to estimate the BSM proposed by Segoviano and Goodhart (2009) and use it to analyze the financial stability of the main banks in any country or region, to enable tracking of the relative stability of this portfolio of banks over time and compare cross-sections of comparative groupings. This framework offers several advantages:

- It provides measures for analyzing (defining) stability from three different, but complementary perspectives.
- It can be constructed using a very limited set of data, specifically, the empirical measurements of default probabilities for individual banks. These measures can also be estimated using alternative approaches, depending on data availability. The data set needed for estimates is available in many developed and developing countries, provided there is reasonable data on individual bank PoDs.
- It includes banks' default interdependence structure (copula function), thus capturing linear and nonlinear default dependencies among the main banks in a system.
- It allows quantification of changes in banks' default interdependence structure at specific points in time. Thus, it can be useful to quantify empirically observed increases in dependencies at times of distress and relax the assumption of fixed correlations across time, commonly used in risk measurement models.

In the empirical part of this paper, we discussed the application of this methodology to several country and regional examples, using information available up to February 2009. This flexibility is useful to monitoring bank stability, as cross-border financial linkages increase and become more significant, as apparent during the financial market turmoil of recent months. Thus, monitoring bank stability cannot stop at national borders.

APPENDIX A
Copula Functions

Let x and y be two random variables with individual distributions $x \sim F$, $y \sim H$ and a joint distribution $(x, y) \sim G$. The joint distribution contains three types of information. Individual (marginal) information on the variable x, individual (marginal) information on the variable y and information on the dependence between x and y. To model the dependence structure between the two random variables, the copula approach sterilizes the marginal information on x and y from their joint distribution, isolating the dependence structure as a result. Marginal information is sterilized by transforming the distribution of x and y into a uniform distribution; U(0,1), which is uninformative. Under this distribution the random variables have an equal probability of taking a value between 0 and 1 and a zero probability of taking a value outside [0,1]. Therefore, this distribution is typically thought of as being uninformative. To transform x and y into U(0,1) we use the probability integral transformation (PIT).

Under PIT, two new variables are defined as $u=F(x)$, $v=H(y)$, both distributed as U(0,1) with joint density $c(u,v)$. Under the distribution of transformation of random variables (Cassella and Berger, 1990), the copula function $c(u,v)$ is defined as:

$$c(u,v) = \frac{g\left[F^{(-1)}(u), H^{(-1)}(v)\right]}{f\left[F^{(-1)}(u)\right]h\left[H^{(-1)}(v)\right]}, \tag{A1}$$

where g, f, and h are defined densities.

From equation (A1), we see that copula functions are multivariate distributions, whose marginal distributions are uniform on the interval [0,1]. Therefore, since each of the variables is individually (marginally) uniform (that is, their information content has been sterilized via PIT), their joint distribution will only contain dependence information. Rewriting equation (A1) in terms of x and y we get

$$c\left[F(x), H(y)\right] = \frac{g(x,y)}{f(x)h(y)}. \tag{A2}$$

From equation (A2), we see that the joint density of u and v is the ratio of the joint density of x and y to the product of the marginal densities. Therefore, if the variables are independent, equation (A2) is equal to one.

Sklar's Theorem

The following theorem was developed by Sklar (1959) and is known as Sklar's Theorem. It is relevant to copula functions, and is used in all applications of copulas. If G is a joint distribution function with marginals F and H, then a copula C exists for all x, y in $\mathbb{R}$,

$$G(x,y) = C\left[F(x), H(y)\right]. \tag{A3}$$

If F and H are continuous, then C is unique; otherwise, C is uniquely determined on Ran$F \times$ Ran$H$. Conversely, if C is a copula and F and H are distribution functions, then the multivariate function G defined by equation (A3) is a joint distribution function with univariate margins F and H. Thus, the dependence structure is completely characterized by the copula C (Nelsen, 1999). Nelsen also provides the following corollary to Sklar's theorem.
Corollary: Let G be any joint distribution with continuous marginals F and H. Let $F^{(-1)}(u)$, $H^{(-1)}(v)$ denote the (quasi) inverses of the marginal distributions. Then there exists a unique copula C: [0,1] x [0,1]$\rightarrow$[0,1] such that, $g[F^{(-1)}(u), H^{(-1)}(v)]\forall\in$[0,1] x [0,1]. If the cross partial derivatives of equation (A3) are taken, we obtain:

$$g(x,y) = f(x)h(y)c\left[F(x), H(y)\right]. \tag{A4}$$

The converse of Sklar's theorem implies that we can couple together any marginal distributions, of any family, with any copula function and a valid joint density will be defined. The corollary implies that from any joint distribution we can extract the implied copula and marginal distributions (Nelsen, 1999).

Parametric Copula Functions

In the finance literature, it is common to see the Gaussian copula and the t copula for modeling dependence among financial assets. These are defined as follows (Embrechts, Lindskog, and McNeil, 2003):

Gaussian copula: The copula of the bivariate normal distribution can be written as:

$$C_R^{Ga}(u,v) = \int_{-\infty}^{\Phi^{-1}(u)} \int_{-\infty}^{\Phi^{-1}(v)} \frac{1}{2\pi(1-\rho^2)^{1/2}} \exp\left[-\frac{s^2 - 2\rho st + t^2}{2(1-\rho^2)}\right] dsdt, \qquad \text{(A5)}$$

where ρ is the linear correlation coefficient of the corresponding bivariate normal distribution, and Φ^{-1} denotes the inverse of the distribution function of the univariate standard normal distribution.

***t* copula:** The copula of the bivariate *t*-distribution with υ degrees of freedom and correlation ρ is:

$$C_{\upsilon\rho}^{t}(u,v) = \int_{-\infty}^{t_\upsilon^{-1}(u)} \int_{-\infty}^{t_\upsilon^{-1}(v)} \frac{1}{2\pi(1-\rho^2)^{1/2}} \left[1 + \frac{s^2 - 2\rho st + t^2}{\upsilon(1-\rho^2)}\right]^{-(\upsilon+2)/2} dsdt, \quad \text{(A6)}$$

where $t_\upsilon^{-1}(v)$ denotes the inverse of the distribution function of the standard univariate *t*-distribution with υ degrees of freedom. As it can be seen, this copula depends only on ρ and υ.

Appendix B
CIMDO copula

To provide a heuristic explanation of the CIMDO copula, we compare the copula of a bivariate CIMDO distribution and a bivariate distribution of the form that the prior density in the entropy functional would take, for example, a t-distribution. First, we recall from equation (4) that copula functions are defined as

$$c(u,v) = \frac{g\left[F^{(-1)}(u), H^{(-1)}(v)\right]}{f\left[F^{(-1)}(u)\right] h\left[H^{(-1)}(v)\right]}.$$

We then assume that the prior has a density function $q(x,y)$. Thus, its marginal cumulative distribution functions take the form

$$u = F(x) = \int_{-\infty}^{\bar{x}} \int_{-\infty}^{+\infty} q(x,y)\, dy dx \text{ , and}$$

$$v = H(y) = \int_{-\infty}^{\bar{x}} \int_{-\infty}^{+\infty} q(x,y)\, dx dy \text{ , where } u = F(x) \Leftrightarrow x = F^{-1}(u),$$

and $v = H(y) \Leftrightarrow y = H^{-1}(v)$.

Therefore, its marginal densities take the form

$$f(x) = \int_{-\infty}^{+\infty} q(x,y)\, dy, \text{ and}$$

$$h(y) = \int_{-\infty}^{+\infty} q(x,y)\, dx.$$

Substituting these into the copula definition, we obtain the copula of the prior,

$$c_q(u,v) = \frac{q\left[F^{-1}(u), H^{-1}(v)\right]}{\int_{-\infty}^{+\infty} q\left[F^{-1}(u), y\right] dy \int_{-\infty}^{+\infty} q\left[x, H^{-1}(v)\right] dx}. \tag{B1}$$

Similarly, we assume that the CIMDO distribution with $q(x,y)$ as the prior takes the form

$$\widehat{p(x,y)} = q(x,y)\exp\left\{-\left[1+\hat{\mu}+(\hat{\lambda}_1\chi_{[x_d^x,\infty)})+(\hat{\lambda}_2\chi_{[x_d^y,\infty)})\right]\right\}.$$

We also define $u = F_c(x) \Leftrightarrow x = F_c^{-1}(u)$, and $v = H_c(y) \Leftrightarrow y = H_c^{-1}(v)$. Its marginal densities take the form

$$f_c(x) = \int_{-\infty}^{+\infty} q(x,y)\exp\left\{-\left[1+\hat{\mu}+(\hat{\lambda}_1\chi_{x_d^x}(x))+(\hat{\lambda}_2\chi_{x_d^y}(y))\right]\right\}dy,$$

and

$$h_c(y) = \int_{-\infty}^{+\infty} q(x,y)\exp\left\{-\left[1+\hat{\mu}+(\hat{\lambda}_1\chi_{x_d^x}(x))+(\hat{\lambda}_2\chi_{x_d^y}(y))\right]\right\}dx.$$

Substituting these into the copula definition, we obtain the CIMDO copula,

$$c_c(u,v) = \frac{1}{\int_{-\infty}^{+\infty} q\left[F_c^{-1}(u),y\right]\exp\left[-\hat{\lambda}_2\chi_{x_d^y}(y)\right]dy} \times \frac{q\left[F_c^{-1}(u),H_c^{-1}(v)\right]\exp\left[-(1+\hat{\mu})\right]}{\int_{-\infty}^{+\infty} q\left[x,H_c^{-1}(v)\right]\exp\left[-\hat{\lambda}_1\chi_{x_d^x}(x)\right]dx}. \tag{B2}$$

Equation (B2) shows that the CIMDO copula is a nonlinear function of $\hat{\mu}$, $\hat{\lambda}_1$, and $\hat{\lambda}_2$, which change as the PoDs of the banks under analysis change. Therefore, the CIMDO copula captures changes in PoDs, as these change at different periods of the economic cycle.

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Funding Liquidity Risk in a Quantitative Model of Systemic Stability

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The global financial crisis of 2007–09 has illustrated the importance of including funding liquidity feedbacks in any model of systemic risk. This paper illustrates how we have incorporated such channels into a risk assessment model for systemic institutions (RAMSI), and it outlines the Bank of England's plans to use RAMSI to sharpen its assessment of institution-specific and systemwide

All authors are with the Bank of England except Prasanna Gai, who is with the Australian National University, and Nada Mora, who is with the Federal Reserve Bank of Kansas City. The RAMSI project represents a major investment of Bank of England resources, and we are grateful to many people both inside and outside the Bank of England for their contributions. In particular, the National Bank of Austria has been very generous in providing guidance and significant analytical contributions. The analysis in this paper has benefited from encouragement and contributions from Viral Acharya, Niki Anderson, Marnoch Aston, Richard Barwell, Emily Beau, Michael Boss, John Carmichael, Ethan Cohen-Cole, Geoff Coppins, Sebastiano Daros, Paul Doran, Mathias Drehmann, John Elliott, Helmut Elsinger, David England, Phil Evans, Antonella Foglia, Celine Gauthier, Brenda Gonzalez-Hermosillo, Charles Goodhart, Andy Haldane, Simon Hall, Jen Han, Florence Hubert, Gregor Irwin, Charles Khan, David Lando, Nigel Jenkinson, Rob Johnson, Charles Kahn, Sandhya Kawar, Will Kerry, Jack Mckeown, Alex McNeil, Andrew Mason, Colin Miles, Pierre Monnin, Haroon Mumtaz, Emma Murphy, Gareth Murphy, Rain Newton-Smith, Joseph Noss, Spyros Pagratis, Andrew Patton, Adrian Penalver, Silvia Pezzini, Laura Piscitelli, Claus Puhr, Victoria Saporta, Til Schuermann, Miguel Segoviano, Jack Selody, Hyun Shin, Steffen Sorensen, George Speight, Marco Stringa, Martin Summer, Ryland Thomas, Dimitri Tsomocos, Iman van Lelyveld, Nick Vause, Lewis Webber, Simon Wells, and Peter Westaway. Harry Goodacre, Tony Lee, and Emma Mattingley provided excellent research assistance.

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vulnerabilities. The model focuses on the health of core banks in the U.K. financial system. For these banks, the model provides a coherent quantitative framework for assessing how shocks transmit through balance sheets, allowing for macro-credit risk, interest and noninterest income risk, network interactions, and feedback effects arising on both the asset and liability side of the balance sheet. Systemic risks stem from the connectivity of bank balance sheets via interbank exposures (counterparty risk); the interaction between balance sheets and asset prices (fire-sale effects); and confidence effects that may affect funding conditions.

Central banks and regulators are increasingly seeking to use formal models to support their financial stability work, and various approaches have emerged in recent years (Jenkinson, 2007). Senior policymakers at the Bank of England have for some time expressed a desire for an integrated approach to assessing systemic risk (Gieve, 2006). Gai and Haldane (2007) provide motivation for a new approach that emphasizes the importance of distinguishing probability and impact when conducting risk assessment work, and the Bank of England's preliminary implementation of such a framework is discussed by Haldane, Hall, and Pezzini (2007).

RAMSI aims to deliver a suite of models that should support a substantial enhancement in the Bank of England's ability to conduct risk assessment in a rigorous and consistent quantitative framework, thus helping to sharpen the analysis of key vulnerabilities and to improve the Bank's capability to influence and strengthen the management of these risks. Internally, RAMSI will support discussions of key risks on a bank-by-bank and systemwide basis, and it will facilitate examining the impact of various policy measures. Externally, the outputs from the suite of models will be a source for communicating risk assessment messages to risk managers in the financial sector, thereby helping shape their attitudes toward risk.

The analytical foundations of RAMSI draw, in particular, on two strands of literature. First, it employs elements of the traditional stress-testing literature, which tend to focus on credit risk on a bank's balance sheet (see Foglia, 2009; Borio and Drehmann, in this volume). Second, it draws on recent theoretical work on modeling systemic financial crises. Allen and Gale (2000) explore the spread of contagion in a banking network, and Cifuentes, Ferrucci, and Shin (2005) examine how default across

the network is amplified by asset price effects. Gai and Kapadia (2010; in this volume) examine the nonlinearities implied by these externalities and suggest that financial innovation may have increased the severity of crises.[1]

The modular approach involves feeding shocks and scenarios from a macroeconomic model through several distinct balance-sheet-based models that describe how risk profiles evolve throughout banks' business operations. It is influenced by the framework developed by the National Bank of Austria (Boss and others, 2006) for the Austrian banking system (see also Elsinger, Lehar, and Summer, 2006a), which integrates balance-sheet-based models of credit and market risk with a network model to evaluate the probability of bank default. In presenting a prototype version of RAMSI, Alessandri and others (2009) extended and developed the single-period Austrian model in a number of dimensions. In a multi-period setting, they incorporated net interest income and feedback effects associated with asset fire sales following bank default.

This paper extends the RAMSI prototype in several ways, including the use of richer balance sheets, a more powerful macroeconomic model, better modeling of credit risk, and a model of noninterest (nontrading) income. The main innovation, however, relates to the role of liability-side feedbacks. We develop a two-pronged framework for modeling funding liquidity risk. In the first stage, we apply an empirical model to project individual bank ratings, and we then use the results to calibrate how funding costs may rise as a bank's position worsens. In the second stage, we calibrate the onset of funding crises and outright closure of funding markets to particular institutions based on a series of indicators. To inform our analysis, we draw on theoretical models, information from banks' own liquidity policies, and evidence both from past episodes of funding stress and from recent experience, including the failure of Northern Rock.

RAMSI's framework is particularly attractive to central banks because of its storytelling capacity. Alternative approaches to the analysis of systemic risk offer particular strengths, either in terms of micro-foundations or in terms of consistency with market-based

1. This result is reinforced by Gai and others (2008), who demonstrate how financial innovation and macroeconomic stability may have intensified the robust-yet-fragile nature of the banking system.

pricing of risk.[2] Although RAMSI's framework relies on reduced-form estimation and behavioral rules of thumb, it offers a flexible and operational means of capturing a wide range of risks and transmission channels, and it allows for a more articulated analysis and interpretation of the outputs of stress-testing exercises.

The structure of the paper is as follows. Section 1 describes the current components of RAMSI and explains how they fit together. Section 2 discusses the aggregate distributions obtained from stochastic simulation and conducts a detailed analysis of a particular realization in which funding liquidity feedbacks contribute to systemwide stress. Section 3 discusses how RAMSI will improve the quality of risk assessment work, and section 4 concludes.

1. The Modeling Framework

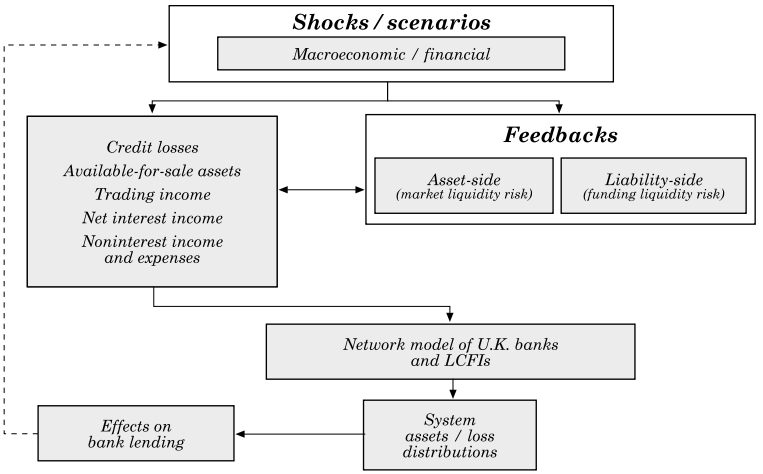
Figure 1 illustrates the modular structure of RAMSI and the mapping from shocks to systemic risk. The transmission dynamics hinge crucially on two factors—the nature and scale of shocks and the structural characteristics of the financial system. In such an environment, balance sheet interdependencies and asset- and liability-side feedbacks make for complex, nonlinear behavior. RAMSI produces asset distributions for individual banks and for the aggregate banking system by linking together the shaded modules presented in figure 1. The unshaded module (that is, feedbacks to the macroeconomy) is mentioned briefly in the conclusion, but it is mainly left for future work. In what follows, we discuss the overall modeling strategy in RAMSI before briefly discussing each of its components.

At the core of RAMSI are detailed end-2007 balance sheets of the ten largest U.K. banks.[3] These link the modules to the structure of

2. For example, Goodhart, Sunirand, and Tsomocos (2006) provide a general equilibrium framework, but the model is stylized and difficult to operationalize. The asset pricing approach, in turn, extracts risk from observed security prices. This approach can be applied to individual banks (Segoviano and Padilla, 2006; Elsinger, Lehar, and Summer, 2006b; Frisell and others, 2007) or to sectors of the economy (Gray, Merton, and Bodie, 2007). These models provide timely updates to banks' risk profiles, albeit on the basis of strong assumptions on market completeness and efficiency. Furthermore, market prices may embed the possibility of official support, so the asset pricing approach may be unable to identify the extent to which intervention helps to mitigate systemic risks (Birchler and Facchinetti, 2007).

3. Membership of the major U.K. banks group is based on the provision of customer services in the United Kingdom, regardless of country of ownership. At year-end 2007, the members were Alliance and Leicester, Banco Santander, Barclays, Bradford and Bingley, Halifax Bank of Scotland, HSBC, Lloyds TSB, Nationwide, Northern Rock, and Royal Bank of Scotland.

Figure 1. RAMSI Framework



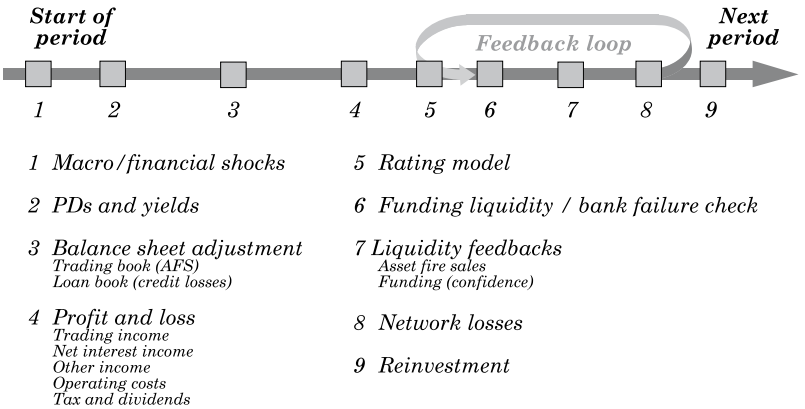
Source: Authors' assessment.

individual U.K. banks. The balance sheets are highly disaggregated, with approximately 650 balance sheet entries (including 400 asset classes and 250 liability classes). Each of the asset and liability classes are further disaggregated into five maturity buckets and six repricing buckets.[4] Data are mainly extracted from regulatory accounts but are supplemented from regulatory returns. This modeling of individual bank balance sheets supports an analytically rich model and allows us to examine, in detail, the likely sources of profits and losses on a disaggregated and aggregated basis. Not all of the balance sheet entries are available, so we use rules of thumb based on other information or extrapolations on the basis of our knowledge of similarities between banks to fill in the data gaps. Much of the granularity arises from decomposition of the trading book and available for sale (AFS) assets. Since the focus of this paper is on the role of funding liquidity risk, we do not model these exposures here. However, this part of the balance sheet has played an important role in the ongoing financial crisis, and we believe that no systemic risk model can credibly ignore it. Trading book and AFS models are currently under development and will be introduced in the next version of RAMSI.

4. We do not have six repricing buckets for each of the five maturity buckets.

The model is run over a three year horizon, which is sufficient time for some adverse shocks to be reflected in credit losses (Bunn, Cunningham, and Drehmann, 2005; DNB, 2006) and is consistent with the horizon central banks often use when stress testing their financial systems (Hagen and others, 2005; Bank of England, 2007; Sveriges Riksbank, 2007). The sequence of events is illustrated in figure 2. Outcomes from a macroeconomic model determine a yield curve and probabilities of default and loss-given default on banks' credit exposures. For each combination of risk factors, we model the first-round effects on each bank, with distinct modules accounting for credit losses, net interest income, other income, and operating expenses.

Figure 2. Model Dynamics[a]



Source: Authors' drawing.
a. The trading book and available-for-sale (AFS) assets are not included in this version of RAMSI.

If a bank's fundamentals deteriorate, its rating may be downgraded, increasing its future funding costs. In severe circumstances, funding conditions may deteriorate to such an extent that the bank is shut out of short-term funding markets. It then fails, triggering a feedback loop. Because of bankruptcy costs, a fraction of the failed bank's assets are lost, reducing the amount available to its creditors on the interbank network. Some of the bank's assets are sold at fire-sale prices, creating asset-side feedbacks that cause remaining banks to suffer temporary (intraperiod) mark-to-market losses. Funding markets suffer confidence contagion that makes banks with similar characteristics to the failed bank more vulnerable

to being shut out of funding markets. If a further bank fails after we account for the second-round effects, then the loop repeats until the default cascade ends.

In the absence of bank failures (or after the feedback loop has completed), we update the balance sheets of surviving banks using a rule of thumb for reinvestment behavior. Banks target prespecified Tier 1 capital ratios, and they invest in assets and increase liabilities in proportion to their shares on their initial balance sheet.

Throughout the paper, we assume that there is no regulatory or other policy intervention, aside from the interest rate response that is endogenous to the macroeconomic model. This is partly because modeling the policy reaction to extreme events is inherently difficult, especially given that there is no single, standard response to financial crises. The model therefore provides an assessment of how the financial system would fare without any policy response. This allows for judgements to be drawn on the potential benefits and costs of intervening.

1.1 The Macroeconomic Model

The link between the macroeconomy and the various risks on banks' balance sheets is central to RAMSI. We use a large-scale Bayesian vector autoregression (BVAR) to capture the evolution of macroeconomic and financial variables. The BVAR is the only source of shocks in RAMSI, thereby preserving a one-for-one mapping from macroeconomic variables to default risk, which is useful for story-telling purposes.[5]

The BVAR is estimated on quarterly data over the sample period from the second quarter of 1972 to the fourth quarter of 2007. The model includes 24 domestic and foreign (U.S. and E.U.) variables (see table 1) and has two lags. We use quarterly growth rates of all variables, barring those denoted with an asterisk. The resulting vector of time series variables to be modeled therefore contains a mixture of levels and growth rates, including the quarterly growth of gross domestic product (GDP), the level of the three-month Treasury bill rate, and so on. Our prior treats every variable in the system as a white noise process centered around a constant. This is a special case of the Minnesota prior popularized by Litterman (1986): essentially,

5. Stress scenarios can be used to determine the impact of adjusting nonmacroeconomic variables and model parameters.

Table 1. List of BVAR Variables

Country or region	*Variable*	
	In quarterly growth rates	*In levels*
United Kingdom	Real GDP	Three-month Treasury bill rate
	CPI inflation	Three-year government bond rate
	£ERI	Ten-year government bond rate
	Real FTSE index, all shares	Unemployment
	Real house prices	Income gearing
	Real commercial prop. prices	Corporate lending
		Three-month LIBOR spread
		Ten-year corporate spread
United States	Real GDP	Three-month Treasury bill rate
	CPI	Three-year government bond rate
Euro area	Real GDP	Three-month Treasury bill rate
	CPI	Three-year government bond rate
World	Real oil prices	
	Real world equity prices	

Source: Authors' compilation.

we adapt the standard Minnesota prior to the case where all unit roots have been eliminated by data transformations.[6]

The BVAR performs well according to the usual diagnostics. First, it has reasonable in-sample fit, capturing much of the variation over time in most series (the average R squared across the 24 equations was 66 percent). The equations for asset prices had the poorest fit, including equities, the sterling exchange rate index (ERI), and particularly oil prices (R squared of 12 percent). Second, the forecasts are, for the most part, reasonable: most variables are projected to either regress back to their average historical growth rates or to gradually converge on their sample means. Third, the model also produces reasonable impulse responses following shocks to U.K. GDP, U.K. three-month interest rates, U.K. house prices, and real oil prices.

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

For simplicity, we approximate the yield curve by linearly interpolating the short- and long-term interest rates implied by the BVAR (two for the United Kingdom and one each for the euro area and the United States). This is the source of all risk-free rates used in the model. Finally, since the BVAR does not forecast the spread on the London interbank offered rate (LIBOR) particularly well, we currently assume that it evolves according to the path implied by forward spreads.

1.2 First-Round Impact on Banks

In this section we assess the first-round impact of shocks on banks, before the impact of any systemic interactions.

1.2.1 Credit risk

The credit risk module treats aggregate default probabilities (PDs) and loss given default (LGD) as a function of the macroeconomic and financial variables from the BVAR. Credit losses are derived as the product of the relevant aggregate PD times LGD times each bank's total exposure to the sector.[7] We adjust the aggregate write-off rate for each bank to account for heterogeneity in the riskiness of banks' portfolios.[8] We model credit losses arising from exposure to U.K. households (through mortgages, credit cards, and other unsecured borrowing), U.K. corporates, plus households and corporates in the United States, the euro area and the rest of the world.[9] For brevity, we only report results for U.K. mortgages and corporate loans.

Basing the model on Whitley, Windram, and Cox (2004), we relate the PD on a representative pool of mortgages to the unemployment rate, the level of income gearing (that is, interest payments relative to disposable income), and undrawn equity in housing stock (that is, the residual proportion of housing wealth net of the stock of

7. That is, we model expected credit losses and trace out variation in expected credit losses driven by macroeconomic fundamentals.

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

9. Data availability poses a major challenge. It would be desirable to capture sectoral concentrations and lumpiness in corporate exposures by modeling a finer breakdown of exposures (such as commercial property lending). Currently, our assumption is that portfolios are infinitely granular.

mortgage debt). Our dependent variable is the fraction of borrowers who are three months or more in arrears. We model arrears as they provide a forward-looking indicator of actual defaults. We estimate a transition rate based on the average historical relationship between these variables. The model is estimated on a sample running from the early 1980s, reflecting the structural change in retail credit markets following the removal of direct controls on bank lending in 1980 (the so-called corset). The LGD on this pool is assumed to be driven by residential property prices.

Our preferred model of the corporate liquidations rate is driven by real output growth, the real (ex post) cost of borrowing, commercial property prices, and a measure of the cyclical variation in corporate debt (based on Vlieghe, 2001). The LGD on a corporate loan is assumed to depend on the value of commercial property prices.

The estimated coefficients in both equations are all signed according to our priors. Both models capture the broad movements in the data reasonably well, but there are clear areas for improvement. The mortgage arrears equation, for instance, only accounts for around half of the pick up in arrears in the early 1990s, and the performance of the corporate PD equation deteriorates from 2002 onwards.[10]

1.2.2 Net interest income

For most of the loan book, interest income is modeled endogenously. Banks price their loans 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. However, banks' repricing ability is constrained by the maturity structure of their balance sheets. Since assets and liabilities typically do not have matched maturities, these constraints generate significant income risk. The possibility of shifts in the yield curve intensifies this risk.

We use the risk-neutral asset pricing model of Drehmann, Sorensen, and Stringa (2008) to consistently capture both sources of income risk. Consider a risky asset, A, with a repricing maturity equal to T, implying that the asset pays a fixed coupon C over the next

10. Possible explanations include the (until recently) prolonged stability of the macroeconomy; the cleansing effect of earlier recessions; legislative changes (namely, the 2000 Insolvency Act and the 2002 Enterprise Act); and (until recently) the easy availability of credit.

T periods. The economic value of the asset today is the risk-adjusted discounted value of future coupon payments and the principal:

$$\mathrm{E}V(A_0) = \sum_{t=1}^{T} D_t C A_0 + D_T A_0, \tag{1}$$

where the discount factors are given by

$$D_t = \prod_{l=1}^{t} (1 + R_{l-1,l})^{-1} \tag{2}$$

and

$$R_{l-1,l} = \frac{r_{l-1,l} + PD_{l-1,l} * LGD_{l-1,l}}{1 - PD_{l-1,l} * LGD_{l-1,l}},$$

and where $r_{l-1,l}$, $PD_{l-1,l}$, and $LGD_{l-1,l}$ represent, respectively, the forward risk-free interest rate, expected PD, and expected LGD between time $l-1$ and l.[11] We can use the first equation to calculate a fair time-zero coupon that guarantees that $\mathrm{E}V(A_0) = A_0$:

$$C = \frac{1 - D_T}{\sum_{t=1}^{T} D_T}. \tag{3}$$

Whenever the bank can update C (that is, at time T, $2T$,...), it will do so using the equation above, so that expected interest income covers expected losses and book and economic value coincide. Between 0 and T, though, interest rates, PDs, and LGDs may change, whereas the coupon is fixed: any change in discount factors that is unexpected as of time zero will thus prevent the zero-profit condition from holding. For each bank, we use balance sheet information to determine the fraction of assets and liabilities that can be repriced at any point in time. The model implies that the pricing structure of the balance sheet—particularly the mismatch between assets and liabilities—influences a bank's vulnerability to interest rate and PD shocks.

11. The risk-free yield curve is known at the time of pricing; we assume that banks take future PDs and LGDs to be equal to the most recent observations.

The model-implied coupons are calibrated to better accord with actual observed spreads, as these may also partly reflect compensation for fixed costs associated with arranging loans and oligopolistic profits derived by banks. In particular, for household and nonfinancial sector corporate assets, the model-implied coupon is increased by 50 basis points.

For other parts of the balance sheet, including all of the liability side, we simply calibrate spreads based on market rates and other data. For example, we assume that interbank assets and liabilities receive or pay the risk-free rate plus the LIBOR spread, while banks pay negative spreads relative to the risk-free rate on some household and corporate deposits (if the negative spread implies a negative interest rate, the interest rate paid is assumed to be zero). As discussed below, spreads on certain liability classes may also depend on the rating of the bank in question.

1.2.3 Noninterest (nontrading) income and operating expenses

Noninterest, nontrading income (henceforth noninterest income) was just under half of U.K. banks' operating income in 2007.[12] It includes fees and commissions (see table 2). Stiroh (2004) finds noninterest income to be procyclical, which appears plausible given that its components include securitizations. Bank-specific and structural determinants may also be important. The rise in the share of noninterest income may be seen in the context of new technologies (such as internet fees), financial derivatives, loan securitizations, and the sale of back-up lines of credit. Capital is not required for many such fee-based activities, even though some, such as derivatives and trust services, take place on balance sheet, so increased reliance on noninterest income could be associated with higher leverage (DeYoung and Rice, 2004).

12. One reason for separating the modeling of trading income from that of the other components of noninterest income is that trading income is the most volatile. It contributes to a large part of the variance of total noninterest income, which itself has increasingly contributed to the variance of overall operating income growth. Stiroh (2004) shows that for U.S. banks, the noninterest income contributed 80 percent of the volatility of operating income in the 1990s.

Table 2. U.S. and U.K. Noninterest Income and Expenses[a]
Ratio of operating income

United States	*1984–89*	*1990–99*	*2000–07*
Net interest income	0.72	0.64	0.57
Noninterest income	0.28	0.36	0.43
Fiduciary	0.05	0.05	0.05
Service charge	0.06	0.07	0.07
Trading	0.02	0.03	0.03
Other	0.15	0.21	0.27
Noninterest expenditure	0.68	0.64	0.59
Noninterest, nontrading income	0.26	0.33	0.40
United Kingdom[b]	*1997–2003*	*2004–06*	*2007 interim*
Net interest income	0.58	0.42	0.39
Noninterest income	0.43	0.58	0.61
Net fees and commissions	0.27	0.20	0.21
Dividend income	0.003	0.004	0.005
Dealing profits	0.05	0.11	0.13
Other	0.10	0.27	0.26
Noninterest expenditure	0.56	0.62	0.59
Noninterest, nontrading income	0.38	0.47	0.48

Source: Authors' calculations.
a. The components of noninterest income are not directly comparable between the United States and the United Kingdom. For example, fees and commissions are included in other noninterest income in the United States.
b. In the United Kingdom, the change to International Financial Reporting Standards (IFRS) in 2004 boosted the share of insurance income. For example, Lloyds TSB's noninterest income as a share of its operating income jumped from 47 percent in 2003 to 74 percent in 2004.

Data paucity and inconsistencies rule out estimation based on U.K. data, so we instead use U.S. data (see table 2). This seems reasonable given the similarities between the United Kingdom and the United States and, in particular, the similar shares of noninterest income in operating income (around 42 percent for U.K. banks and 38 percent for U.S. banks). As in Stiroh (2004), we use aggregate quarterly U.S. data that covers over 7,000 FDIC-insured commercial banks in the period from the first quarter of 1984 to the third quarter of 2007. The use of aggregate data prohibits a search for bank-specific effects.

The results for the favored equation are shown below. As in Stiroh (2004), noninterest income is quite strongly procyclical. A one percentage point increase in real GDP above baseline implies

that real noninterest income rises by 2.7 percentage points initially and 2.0 percentage points eventually.[13] We find insufficiently strong evidence for factors such as balance sheet asset growth, equity returns, and equity volatility to include them in RAMSI. However, some specifications (not shown) provided evidence that noninterest income increases with leverage and decreases with the slope of the yield curve.

$$\begin{aligned}\Delta\ln(\text{Noninterest income}_t) = {} & \underset{(0.27)}{0.003} - \underset{(2.94)}{0.338}\Delta\ln(\text{Noninterest income}_{t-1}) \\ & - \underset{(2.06)}{0.246}\Delta\ln(\text{Noninterest income}_{t-2}) \\ & + \underset{(0.22)}{0.027}\Delta\ln(\text{Noninterest income}_{t-3}) \\ & - \underset{(0.02)}{0.003}\Delta\ln(\text{Noninterest income}_{t-4}) \\ & + \underset{(3.44)}{2.721}\Delta\ln(GDP_t) + \underset{(1.03)}{0.878}\Delta\ln(GDP_{t-1}) \\ & - \underset{(0.13)}{0.114}\Delta\ln(GDP_{t-2}) - \underset{(1.61)}{1.357}\Delta\ln(GDP_{t-3}) \\ & + \underset{(1.19)}{1.003}\Delta\ln(GDP_{t-4}),\end{aligned}$$

where the joint significance of GDP and lagged GDP (p value) is 0.004 and the adjusted R squared is 0.18, based on 90 observations.

We validate the U.S.-based model on U.K. data by checking its forecasting performance. We generate noninterest income forecasts for each U.K. bank based on its initial level and increase that with the predicted values of real noninterest income growth from the estimated equation. When calibrated to U.K. banks, the out-of-sample forecasting performance is satisfactory. Between 2005 and 2007, the model predicts a 16.5 percent increase over the two years, compared with an outturn of 16.2 percent.

For noninterest expenses (that is, operating expenses), we suppose that banks target cost ratios. This is supported by empirical estimates of an equation for noninterest costs based on the same aggregate U.S. data that were used to estimate noninterest income. Costs are found to be less procyclical than operating income, reflecting the proposition that banks are unable to immediately adjust expenses. The equation for operating expenses is

13. We also tried an error correction mechanism specification in an attempt to identify a long-run relationship, but it did not forecast as well as the dynamic equation.

$$\left(\frac{\text{Operating expense}}{\text{Operating income}}\right)_t = \underset{(2.16)}{0.053} + \underset{(23.64)}{0.920}\left(\frac{\text{Operating expense}}{\text{Operating income}}\right)_{t-1} - \underset{(1.45)}{0.487}\, d\ln(GDP_t),$$

where the adjusted R squared is 0.86, based on 94 observations.

1.2.4 Profits, Taxes, and Dividends

To generate plausible profit figures, we assume that each bank earns a trading income that is proportional to the size of its portfolio, using 2007 data to calibrate the ratio. This assumption will obviously become redundant when we introduce trading book and AFS models. Profits are then computed as the sum of all sources of income, net of expenses and credit losses. We deduct taxes and dividends from profits, assuming that the tax rate and ratio of dividends to profits are in line with recent history.

Profits (or losses) after taxes and dividends are assumed to increase (or erode) Tier 1 capital directly. Updated Tier 1 capital ratios may then be computed by dividing capital by risk-weighted assets, where the latter are computed by applying Basel II standardized risk weights or approximations to them when we have insufficient information (such as corporate loans, for which we do not know the ratings of the borrowers).

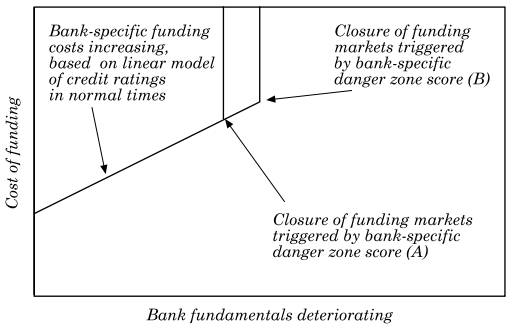
1.3 Funding Liquidity Risk and Bank Failure

The ongoing credit crisis has illustrated starkly how increased funding costs and the closure of funding markets can trigger bank failure. We have integrated two complementary channels to capture funding liquidity effects. First, we apply an empirical model to project individual bank ratings and use the results to calibrate how funding costs may change with the fundamentals of a bank. Second, we use a separate danger zone model in which a range of indicators determine whether a bank suffers stress so severe that it is shut out of unsecured funding markets.

We consider it important to model the outright closure of funding markets in a distinct framework. Figure 3 illustrate this point. Though there may be a relatively linear relationship between a deterioration in bank fundamentals and increased funding costs in

relatively normal times, it is hard to use this approach to identify the closure of funding markets in extreme circumstances, given that this is an inherently nonlinear process and could occur at different ratings and funding costs (A or B), depending on the circumstances. We thus feel that the danger zone approach is more appropriate for identifying the region in which funding markets are likely to shut. Nevertheless, we intend to use the funding cost or ratings model as a cross-check on the danger zone approach.

Figure 3. The Operation of Funding Liquidity Risk



Source: Authors' drawing.

1.3.1 Bank ratings and funding costs

We model banks' funding costs in two stages. First, we use an ordered probit model (adapted from Pagratis and Stringa, 2008) to examine the sensitivity of Moody's senior (long-term) unsecured ratings to a number of key bank performance indicators and macroeconomic variables. The index produces ratings for each bank at each quarter using the estimated coefficients from table 3. Ratings are found to improve under the following conditions: (i) when profitability increases; (ii) when the ratio of (illiquid) customer loans to short-term liabilities is relatively low; (iii) when the bank has a relatively high market share of lending; (iv) when cost efficiency (proxied by operating expenses/total assets) is high; (v) when asset quality (proxied by credit losses/net interest income) is high; (vi) when economy-wide output and credit rise above trend and the yield curve steepens.

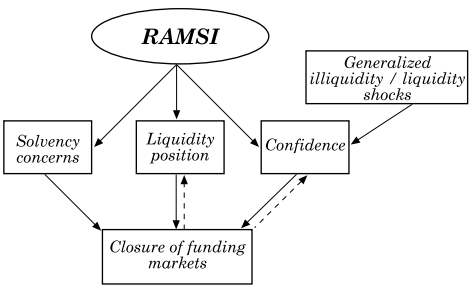
The assigned ratings are mapped to credit spreads using Merrill Lynch's bond indices of U.K. sterling bond spreads associated with different credit ratings. These bank-specific spreads are applied to certain types of wholesale funding (including interbank and other nonretail deposits, commercial paper, certificates of deposit, and subordinated debt). This introduces a key feedback mechanism on the liability side of balance sheets: if a bank gets downgraded, the associated rise in its funding costs will reduce its future profitability, leaving it more vulnerable to future downgrades and, ultimately, to a loss of access to wholesale funding markets.

1.3.2 Modeling the closure of funding markets: A danger zone approach

Modeling the outright closure of funding markets presents significant challenges, both because of the binary, nonlinear nature of liquidity risk and because—notwithstanding recent events—liquidity crises in developed countries are rare events for which data are limited. We therefore adopt a simple, transparent (yet subjective) danger zone approach, under which banks accumulate points as liquidity conditions deteriorate and face the prospect that certain funding markets may close to them as their score crosses particular thresholds.

Figure 4 gives an overview of the approach. Outputs from the rest of the model are mapped into specific indicators of funding stress relating to three key areas that theoretical models (such as Chen, 1999, and Goldstein and Pauzner, 2005) and evidence

Figure 4. Closure of Funding Markets in RAMSI



Source: Authors' assessment.

Table 3. Ordered Probit Estimated Coefficients for the Bank Ratings Model[a]

		Investment-grade bank		*Sub-investment-grade bank*	
Independent variable	*No. lags (in years)*	*Coefficient*	*Robust std. error*	*Coefficient*	*Robust std. error*
Bank financial indicators					
Profitability: 100*(Profits before tax + Credit losses) / Total assets	1	0.200***	0.075	0.048**	0.076
Asset quality: 100*Credit losses / Net interest income	1	–0.002***	0.001	–0.002***	0.001
Cost efficiency: 100*Operating expenses / Total assets	0	–0.127***	0.039	–0.127***	0.039
Funding gap: 100*(Customers loans – Short term liabilities) / Customer loans	0	–0.002***	0.000	0.002***	0.000
Market share: ln(100*Loans / Total loans by banks in the network)	0	0.179***	0.050	0.179***	0.050
Capital dummy: 1 if (Equity / Total assets) falls below target, 0 otherwise	0	–0.261***	0.064	–0.261***	0.064

Table 3. (continued)

Independent variable	*No. lags (in years)*	*Investment-grade bank*		*Sub-investment-grade bank*	
		Coefficient	*Robust std. error*	*Coefficient*	*Robust std. error*
Macroeconomic variables					
Yield curve slope: (ten-year gov. bond rate) – (three-month Treasury bill rate)	1	0.078***	0.030	0.078***	0.030
Economic downturn dummy: 1 if real output gap is negative, 0 otherwise	1	0.054	0.084	0.054	0.084
Credit boom dummy: 1 if credit gap is positive, 0 otherwise	2	0.038	0.087	0.038	0.087
Economic downturn credit boom	1, 2	–0.222**	0.109	–0.222**	0.109
Sub-investment-grade dummy: 1 if rating Baa2 and below	1	—	—	–3.038***	0.119
Constant	—	6.187***	—	6.187***	—

Source: Authors' calculations.
** Statistically significant at the 5 percent level.
*** Statistically significant at the 1 percent level.
a. The dependent variable is bank senior unsecured rating by Moody's. The model is estimated using a data panel of 1,369 observations, for the period 1999–2006. The data panel includes published accounts data on 293 banks from 33 countries (grouped in 14 regions) and macroeconomic information. The constant (6.187) is the sum of coefficients for the United Kingdom regional dummy (0.441), the Aaa-Aa1 sovereign rating dummy (6.809), a dummy for IFRS reporting by banks (–0.577), and a dummy for the fourth quartile in the banks' sample distribution ranked by total assets. The first column in the table reports the lag structure of explanatory variables in the adapted Pagratis and Stringa (2008) model. For interaction effects, we report two lags, one for each interacting variable. The second column reports the estimated coefficients of explanatory variables in the model. The third column reports White robust standard errors. The fourth column reports the estimated coefficients of interaction effects between explanatory variables and a dummy that takes the value 1 if the bank's previous rating was of sub-investment grade (Baa2 and below) and 0 otherwise. Any insignificant coefficients on the economic downturn dummy and the credit boom dummy are zero in the code.

from case studies and banks' own liquidity policies suggest are important: namely, solvency, liquidity, and confidence. The framework allows for feedback effects. In particular, the closure of certain funding markets to an institution may worsen that bank's liquidity position through snowball effects, whereby the bank becomes increasingly reliant on short-term funding, and may adversely affect similar banks through a pure confidence channel. Recent events highlight how marketwide liquidity factors can also play an important role by affecting confidence and thus contributing to funding stress. To proxy for these factors, the framework captures a greater risk of funding stress in periods when the market interbank spread is elevated.

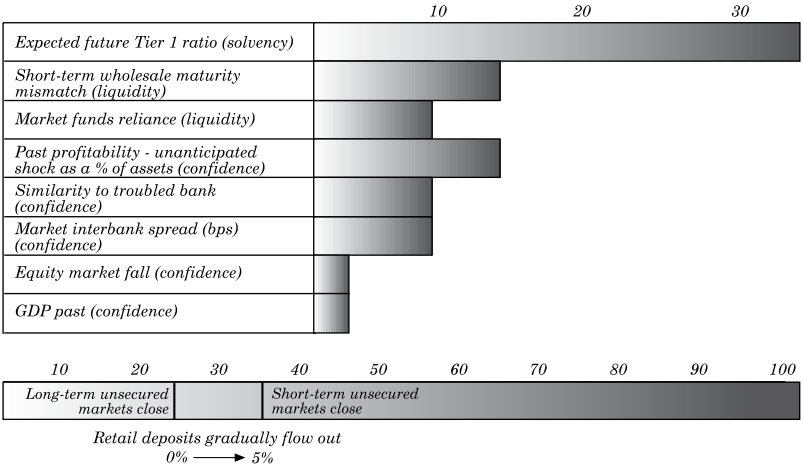
Figure 5 presents the set of eight indicators (with the underlying factor that each is trying to proxy in brackets), along with the aggregation scheme and the thresholds at which short- and long-term unsecured funding markets are assumed to close to the bank.[14] In constructing the weighting, we place roughly equal weight on three main factors that can trigger a funding crises: (i) concerns about future solvency; (ii) a weak liquidity position or funding structure (for example, a high reliance on short-term wholesale unsecured funding); and (iii) institution-specific and marketwide confidence effects, over and above those generated by solvency concerns or weaknesses in liquidity positions. 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.[15]

Currently, the danger zones are incorporated into RAMSI in a simplified way. Since the model does not yet include model-consistent expectations, the current Tier 1 capital ratio is used instead of the expected ratio and the past profitability indicator is ignored, as it is not possible to identify unanticipated losses. The threshold at 25

14. Secured funding markets are discussed below. For simplicity, we do not consider a more detailed breakdown of funding markets (for example, we do not distinguish between foreign and domestic funding markets).

15. The case studies (still work in progress) include both episodes in which banks have failed (such as Franklin National Bank, Continental Illinois, Japanese banks, and Northern Rock) and episodes in which banks have survived (including Lehman Brothers during the LTCM crisis, Countrywide, and Société Générale following the recent fraud).

Figure 5. Danger Zones: Basic Structure



Source: Authors' drawing.

points is also ignored, and banks are simply assumed to default if their danger zone score reaches 35 and short-term secured markets close to them. When fully incorporated, a score of 25 or more will trigger the closure of long-term unsecured funding markets to the bank, which will be able to refinance in short-term unsecured funding markets or take other defensive actions such as selling or repoing assets. There will be no default at this point, but there will be a snowball effect, whereby the increased reliance on short-term funds will affect the bank's score on the maturity mismatch indicator.

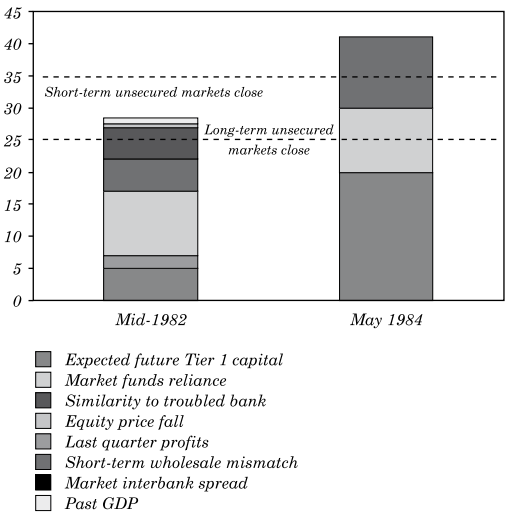
The full danger zone framework will also allow for a number of extensions. First, there will be a gradual outflow of retail deposits after long-term unsecured funding markets close to the bank, such that the outflow reaches 5 percent of retail deposits by the time short-term unsecured markets close. This is intended to reflect behavior of well-informed investors rather than a widespread run (like Northern Rock). Second, we intend to define banks scoring less than five points as safe and allow them to receive funding withdrawn from troubled banks; as such, they will help to close the system by capturing flight-to-quality effects. If there are no safe banks, we will assume funds end up as increased reserves at the central bank. Finally, we plan to extend the framework to cover secured funding markets. For

these, we will assume that if a bank cannot repo assets, it will be able to sell them at the prevailing market price. Critically, however, this could be a fire-sale price and, in some instances, could even be zero, either because there are no buyers in the market or because of potential stigma effects that could be generated by a large asset sale in an illiquid market. The framework will thus highlight the importance of collateral quality in determining how a bank fares if secured funding markets close to it.

1.3.3 Example of a danger zone calibration: Continental Illinois

Case studies indicate that the danger zone approach performs relatively well, especially in terms of capturing the ranking of institutions that are under the most stress. We have considered case studies beyond the very recent crisis. An example is the case of Continental Illinois, which can be divided into two periods, at least in terms of funding liquidity pressure: the closure to it of longer-term domestic funding markets in July 1982 and the global run in May 1984. Figure 6 scores Continental Illinois in each of these periods.

Figure 6. Continental Illinois Danger Zone Points



Source: Authors' calculations.

Continental scores heavily on the market funds reliance indicator, but solvency concerns also played a crucial role. 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 raising solvency concerns, Continental scores points following Penn Square's failure both because of its similarity and because of a significant unanticipated loss from a direct exposure. Overall, Continental scores enough points for the first danger zone threshold to be crossed. Increased reliance on short-term funding then serves to increase Continental's score over the next couple of years. The final trigger for the second run is the fallout from the Latin American debt crisis—which substantially raised future solvency concerns during the first part of 1984 so that by May, Continental exceeds the second danger zone threshold.

1.3.4 Bank failure and bankruptcy costs

As just discussed, banks are assumed to default if they score 35 danger zone points and are shut out of short-term unsecured funding markets. When a bank defaults, we follow James (1991) and suppose that it incurs costs equivalent to 10 percent of its remaining assets. This is also in line with the mean figure reported in Bris, Welch, and Zhu (2006). These bankruptcy costs are designed to capture the direct legal, accounting, and redundancy costs that are incurred upon default. They may also be viewed as capturing the erosion in the real value of a bank's assets that may occur upon default as a result of disruptions to established bank-borrower relationships or the loss of human capital. They imply that even if banks fail with positive shareholder funds, they will be unable to fulfil all of their obligations upon default.

1.4 Second-Round Effects and Contagion

In this section, we assess various channels of systemic feedback that occur when a distressed bank fails. These occur on both the asset and liability side of banks' balance sheets.

1.4.1 Asset-side feedbacks: Fire sales

When a bank is in distress, it may sell assets, opening up the possibility of an important feedback channel operating via asset prices. In the current version of RAMSI, such fire sales only occur after a bank defaults, and not as a defensive action to stave off failure. A failing bank is assumed to liquidate all its available-for-sale (AFS) assets. The fire-sale discount lasts for one quarter, and the resulting fall in asset prices may lead other banks to incur mark-to-market losses; hence in extreme circumstances, these banks may then also fail.

The associated price impact given by equation (4) is applied to other banks' AFS assets. Consistent with Duffie, Gârleanu, and Pedersen (2006), we take the relationship between prices and the magnitude of fire sales to be concave. For asset j, the fire-sale equation is

$$P_j' = \max\left\{0, P_j\left[2 - \exp\left(\theta \frac{S_{ij}}{M_j + \varepsilon_j}\right)\right]\right\}. \tag{4}$$

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

Calibration of the parameters is made difficult by the paucity of empirical analyses that reveal the price impact for a given volume of assets sold in fire sales. Our calibration is guided, in part, by Mitchell, Pedersen, and Pulvino (2007), who consider a fire sale of U.S. convertible bonds by hedge funds in 2005. They estimate that 5 percent of the outstanding stock of U.S. convertible bonds were sold at a maximum price discount of 2.7 percent. Similarly, Coval and Stafford (2007) analyze the price impact of fire sales involving U.S. equity mutual funds. They find an average price

impact of 2.2 percent for the fire sales they identify. Pulvino (1998) focuses on fire sales of aircraft and finds larger price impacts for these assets. He also finds that the price impact varies when the depth of the market fluctuates. However, none of this information is sufficient for precise calibration, since it is not possible to make a direct comparison of the size of the fire sale in relation to the overall market in the study and the potential size in the case of any liquidation of U.K. banks' assets.

Therefore, the calibration is guided both by this empirical evidence and a top-down judgment regarding the plausible impact of a fire sale on capital.[16] The calibration for θ is based on the results presented in Mitchell, Pedersen, and Pulvino (2007). Given θ, a value of market depth M_j is chosen for each of the asset types so that when the U.K. bank with the largest holdings of an asset class in its trading portfolio and AFS assets sells all these assets, it generates prices falls of 2 percent for equities, 4 percent for corporate debt, and 5 percent for asset- and mortgage-backed securities.

1.4.2 Network model

When a bank defaults, counterparty credit losses incurred by other banks are determined using a network model. A matrix of interbank exposures for the major U.K. banks, along with some smaller U.K. institutions and a selection of large, complex financial institutions (LCFIs) is built using reported large exposure data where available. Since we also have information on total interbank asset and liability positions, we then use maximum entropy techniques to fill in missing gaps in the network, ensuring that none of the estimated entries exceed the reporting threshold for large exposures.[17] If any interbank assets or liabilities are unallocated following this procedure, we assume that they are associated with a residual sector that cannot default. Once constructed, the estimated exposure matrix remains static over the forecasting horizon. To clear the network following the default of one or more institutions, we use the Eisenberg and Noe (2001) algorithm. This both determines contagious defaults and returns counterparty credit losses for each institution.

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

17. The techniques adopted are similar to those discussed by Wells (2004), Elsinger, Lehar, and Summer (2006b), and Boss and others (2006).

1.4.3 Feedback loop

After accounting for counterparty credit losses and mark-to-market losses on AFS assets, we update the danger zone scores for banks that survived initially (see figure 2). In the event of another bank breaching the 35-point threshold, we iterate around the network and asset-side feedback mechanism again. If no banks breach the threshold, we update all balance sheets to account for counterparty credit losses. However, we assume that asset prices recover to prefeedback levels, so mark-to-market losses are not carried forward. This reflects the idea that once a crisis has passed, asset prices are likely to return to their fundamental values fairly quickly. A more gradual price adjustment process would impose higher systemic costs on the banking system, and we plan to allow for this in future work.

1.5 Reinvestment

Rules for adjusting balance sheets to account for profits and losses are necessary in a multi-period setting. As noted above, profits (or losses) after taxes and dividends are assumed to increase (or erode) Tier 1 capital. On the asset side, credit losses are simply booked against the relevant exposure for the loss. But other profit and loss items cannot be linked so directly to particular balance sheet lines. Therefore, to rebalance the balance sheet, we adopt a set of mechanical reinvestment rules.[18] If operating income (which includes net interest income, noninterest income, and trading income) exceeds operating expenses, then at the point of rebalancing, liabilities plus capital will exceed assets, and banks reinvest their surplus funds according to the following rules:

—*Rule 1:* Banks have a bank-specific target Tier 1 capital ratio that they aim to meet when investing their funds (and they are not permitted to buy back equity to meet their target);

—*Rule 2:* Subject to rule 1, banks invest in assets in proportion to their shares on the bank's initial balance sheet (for example, mortgage banks will, ceteris paribus, invest in mortgage assets rather than trading assets);

—*Rule 3:* Rule 1 determines total assets after reinvestment and hence the amount of new liabilities that need to be raised; these

18. Rules can be respecified in policy experiments (for example, to assess the impact of targeting leverage or of raising capital).

net new liabilities are allocated in proportion to their shares on the bank's initial balance sheet.

In the current version of RAMSI, defensive actions in response to declines in capital are very limited. When a bank's operating expenses exceed its operating income (so that assets exceed liabilities plus capital at the point of rebalancing), we assume that the bank is unable to disinvest or raise capital. Rather, it raises new liabilities according to rule 3. The reinvestment rule therefore has the benefit of transparently demonstrating the implications of not taking mitigating actions in the face of losses. This is not necessarily realistic, however. For example, an alternative specification would allow banks to disinvest when making losses; this would reduce the likelihood of the bank suffering a liquidity crisis, but it would introduce a further channel of macroeconomic feedbacks.

The primacy of the Tier 1 capital ratio rule is justifiable, first, because five U.K. banks (namely, Barclays, Bradford and Bingley, Halifax Bank of Scotland, HSBC, and Royal Bank of Scotland) publish a Tier 1 capital ratio target; and, second, because the mean ratio of capital to risk-weighted assets for the major U.K. banks was relatively stable in recent years (up to 2007) and institution-specific standard deviations of this ratio were low. For banks that have not published target capital ratios, we assume that they target a capital ratio equal to their end-2007 number.

We are motivated to choose neutral assumptions regarding portfolio allocation, and the second and third rules are based on the presumption that initial balance sheets represent desirable equilibrium outcomes that banks seek to preserve in the face of changes in size. Drastic changes in portfolio are typically associated with a change in the bank's business model. Within a given business model, the rules seem reasonable, especially over the three year horizon considered in this paper.

The portfolio allocation rules are not entirely neutral, however. The liability rule precludes banks from responding to changes in funding costs. On the asset side, our assumed rule precludes the possibility that banks may skew their reinvestment toward areas in which they have recently been most profitable, which may understate the risk. Following positive macroeconomic outcomes, risky assets tend to generate the most profits and increase most in value. Risks would therefore accumulate more quickly were we to employ an alternative reinvestment rule in which banks reinvested profits in proportion to the nominal value of assets held

on the balance sheet in the most recent period (rather than the initial period in our rule). We intend to conduct further validation to guide such choices.

There is no leverage target, so our reinvestment rules allow leverage to be determined according to developments elsewhere in RAMSI. As pointed out by Adrian and Shin (2008), leverage may be procyclical when positive macroeconomic outcomes lead to a decline in the measured riskiness of banks' existing assets (such as a decline in value at risk or a fall in Basel II risk weights). Such procyclicality will be built into RAMSI when we introduce endogenous Basel II risk weights that adjust to changes in PDs. Conversely, if banks choose to purchase relatively risky assets (with high risk weights), then leverage rises relatively *less*, since banks can achieve their Tier 1 capital ratio targets by purchasing fewer assets than if they purchase assets with lower or zero risk weights, such as government bonds.

2. Simulations

We use data up to the fourth quarter of 2007 (so that all balance sheet information is on the basis of end-2007 data) and run 500 simulations on a three-year forecast horizon stretching to the end of 2010. The BVAR is currently the only source of exogenous randomness in the stochastic simulations; each simulation is thus driven by a sequence of macroeconomic shocks drawn from a multivariate normal distribution.[19] It should be stressed, however, that the results are illustrative, reflecting model properties in this preliminary version rather than being the authors' view of likely responses of the banks in question.

2.1 Aggregate Results

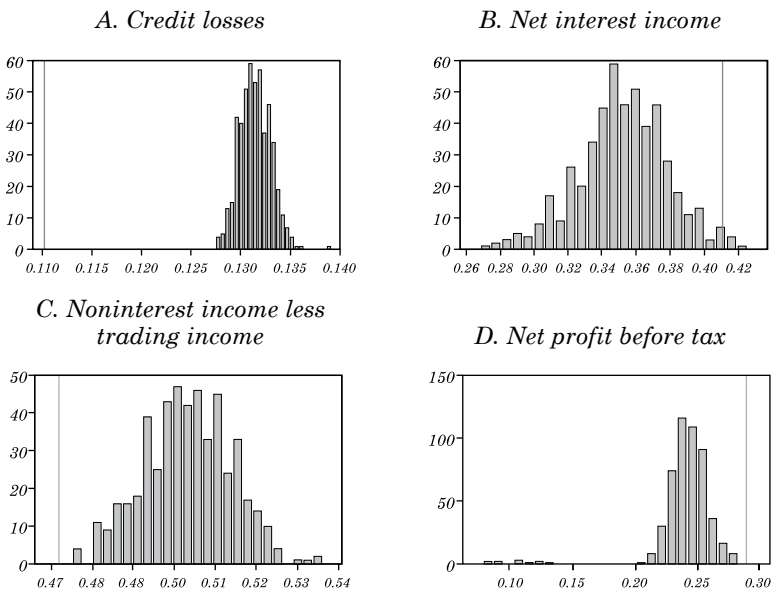
Throughout this section, we discuss results for the U.K. banking system in aggregate. Since individual banks' balance sheets are at the core of RAMSI, the model produces a rich set of information and may be used both to obtain baseline projections for specific institutions and to analyze their performance under stress. Such

19. 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.

information can be used to assess the vulnerability of particular institutions to different risks and may thus feed into the internal institution-specific risk assessment work undertaken by regulators and central banks.

Figure 7 shows the simulated distributions of some key profit and loss items. For each variable, we calculate aggregate cumulative figures for the first year by adding over banks and quarters, and we normalize by aggregate 2007 capital (that is, by capital at the beginning of the period). The vertical line represents the corresponding figures from the 2007 published accounts, normalized by 2006 capital levels.

Figure 7. Simulated Distributions for Profit and Loss Items[a]
Percent of aggregate 2007 capital



Source: Authors' calculations.
a. All items are cumulative for the first forecast year.

Panel A shows that credit risk is projected to increase in 2008, reflecting a worsening of the macroeconomic outlook. However, since our credit risk model abstracts from portfolio concentrations (see section 1.3.1), we arguably underestimate the variance of the credit

risk loss distribution. Net interest income is projected to be weaker than 2007, reflecting contractual frictions that prevent banks from instantaneously passing on higher funding costs to their borrowers. The variance of net interest income may be unrealistically high, as the model does not incorporate hedging of interest rate risk.[20] Noninterest income (panel C) remains high, with a median projection above the reported 2007 level; this variable is procyclical, but it adjusts relatively slowly to macroeconomic changes. The net impact on banks' profitability is summarized in the net profit chart (panel D). Profits were projected to be weaker than in 2007, and there is some evidence of bimodality, insofar as there are a number of observations in the extreme tail of the distribution, which are typically associated with one or more banks defaulting.

2.2 Dissecting the Tail: The Role of Funding Liquidity and Contagion

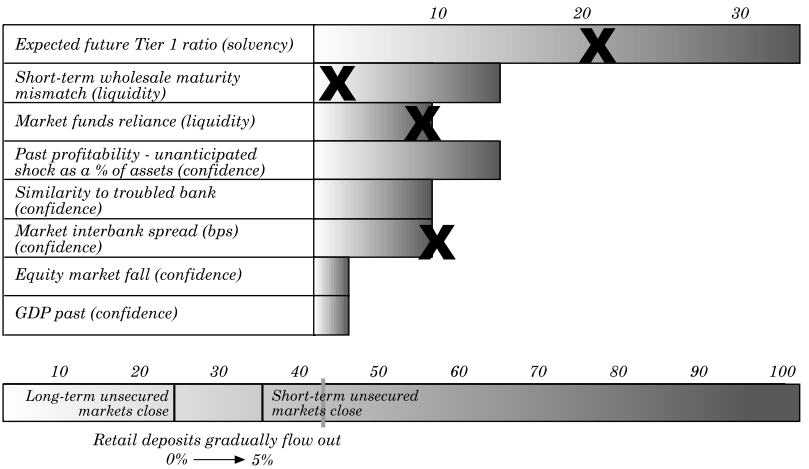
The crisis afflicting banks in the U.K. and internationally has illustrated the importance of funding liquidity. By their nature, the aggregate cumulative distributions in figure 7 mask bank-by-bank heterogeneity. In bad draws taken from the BVAR, some banks incur large losses in some quarters or scenarios, which can erode those banks' Tier 1 capital ratios and increase their danger zone points. With some banks scoring points on the liquidity indicators, the increased solvency concerns can, in extreme cases, be sufficient for a bank's score to reach 35 points, leading to the closure of short-term unsecured funding markets to that institution and its default. Note that the introduction of funding liquidity risk into the framework is critical here. Looking at capital alone, the defaulting banks remain well above the 4 percent regulatory minimum. Nevertheless, a combination of mild solvency concerns, a weak liquidity position, and elevated market interbank spreads is sufficient for wholesale depositors to withdraw funding.

The crosses in figure 8 show danger zone scores for a defaulting bank. The bank fails because it scores points on a range of indicators, including the Tier 1 capital ratio indicator, but its weak liquidity position, captured in the second and third indicators, contributes to its failure. As such, it is clear that the inclusion

20. Banks can be penalized under the second pillar of Basel II for not hedging interest rate risk.

of danger zones in the framework makes banks more vulnerable. The results accord with reality in the sense that funding liquidity crises are triggered by a mixture of factors and can occur even if the bank is perceived to be solvent.

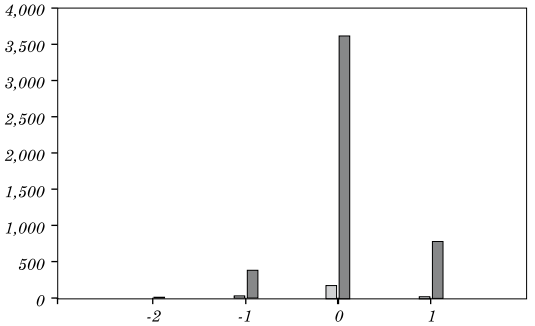
Figure 8. Danger Zone Scores for a Defaulting Bank



Source: Authors' drawing.

Contributing to bank heterogeneity are bank-specific funding spreads that depend on bank ratings. A bank is more likely to be downgraded as profitability falls and its capital falls below target. This serves to raise its funding costs, hurting profits further and making the bank more vulnerable to subsequent default. We observe this feedback relationship in figure 9. The figure shows two distributions for bank rating changes at the end of the forecast horizon or at the point of default, relative to the initial rating. The total number of observations is therefore 500 simulations multiplied by ten banks. The light-shaded distribution is for scenarios in which the bank does not default, and the black-shaded distribution is for scenarios in which the bank defaults. As we expect, the default distribution has more of its mass at lower ratings than does the nondefault distribution.

Figure 9. Rating Distribution: Cumulative Change[a]



Source: Authors' calculations.
a. Bank scenarios for the twelfth quarter, relative to the initial distribution. Gray bars represent ratings for nondefaulting bank scenarios; black bars depict ratings for defaulting bank scenarios.

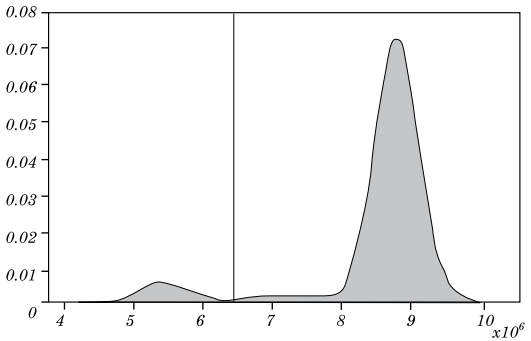
Figure 10 shows the distribution of total assets in the last quarter of the simulation and the average aggregate return on assets (RoA) over the whole horizon. These figures highlight the role of contagion in RAMSI. The distributions are bimodal, with a main peak associated with a healthy banking sector and a considerably smaller second peak in the left tail.[21] This is a direct consequence of bankruptcy costs and, in particular, network and asset-side liquidity feedbacks: since fundamental defaults can generate contagion, extreme negative outcomes become relatively more likely beyond a certain threshold than moderate negative outcomes. This result captures a phenomenon that is commonly perceived as a key feature of financial risk.

The extent to which there is contagion in simulations in the left tail is highlighted by the evolution of the danger zone points. For example, table 4 presents the build up of points for two other banks following the failure of the bank shown in figure 8. As already discussed, this bank (Bank 1) defaults in a fundamental sense because it receives a danger zone score greater than 35. Prior to the failure of Bank 1, Bank 2 only has a danger zone score of 26.5. However, it is perceived to be so similar to Bank 1 that it is tipped into default by this pure confidence effect. Contagion

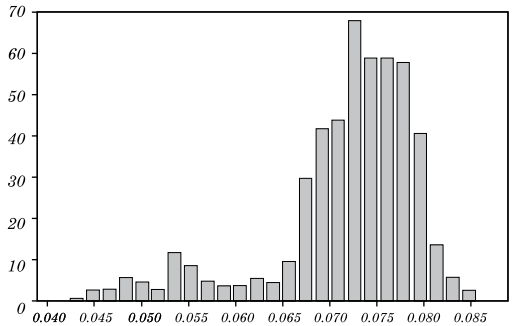
21. The bimodality is qualitatively robust and crucial feature of the model. See Alessandri and others (2009) for more discussion of this bimodality.

Figure 10. Total System Assets and Return on Assets

A. Total system assets: Final forecast quarter



B. Return on assets: Twelve-quarter mean



Source: Authors' calculations.

then extends to Bank 3, which also suffers because of its perceived similarity to the failed banks. Moreover, the failure of Bank 2 and the associated fire sale of its assets cause Bank 3 to incur significant interbank and mark-to-market losses that eat into its capital. Indeed, of all the banks in the network, Bank 3 suffers the greatest counterparty credit loss as a percentage of its Tier 1 capital prior to the default of Bank 1 as a result of the failure of Bank 2. Both interbank and mark-to-market losses triggered by fire-sales are important sources of contagion. This process clearly illustrates how funding liquidity problems at one bank can spread to other banks in tail simulations.

Table 4. Funding Liquidity and Contagion

	Bank 1	*Bank 2*		*Bank 3*		
Variable	*Initial*	*Initial*	*After one default*	*Initial*	*After one default*	*After two defaults*
Expected future Tier 1 ratio	20.5	0.0	0.0	0.0	0.0	2.0
Short-term wholesale maturity mismatch	2.0	13.0	13.0	8.0	8.0	8.0
Market funds reliance	9.0	3.5	3.5	8.0	8.0	8.0
Past profitability	0.0	0.0	0.0	0.0	0.0	0.0
Similarity to troubled bank	0.0	0.0	9.0	0.0	7.0	10.0
Market interbank spread	10.0	10.0	10.0	10.0	10.0	10.0
Equity market fall	0.0	0.0	0.0	0.0	0.0	0.0
Past GDP	0.0	0.0	0.0	0.0	0.0	0.0
Total	41.5	26.5	35.5	26.0	33.0	38.0

Source: Authors' calculations.

3. Policy Applications

The ultimate goal for RAMSI is to sharpen and add analytical rigor to the Bank of England's risk assessment work. To be successful, the model must provide a well-grounded narrative of how potential risks may play out. And to improve external communication, it needs to use metrics that are familiar to supervisors and risk managers. This section assesses some channels through which improvements will transpire and highlights some further issues in using RAMSI for policy analysis.

—*Fan charts:* Aggregate and bank-specific fan charts will be developed for a wide variety of financial variables (including losses, lending, credit spreads, and so on).[22] In producing fan charts, we face a potential trade-off. On the one hand, there are benefits from improving the accuracy of our fan charts by including additional sources of randomness to that arising from the BVAR, for example, from the PD equations and liquidity risk. Such a distribution is arguably more likely to resemble that produced by commercial banks' own risk managers. On the other, increasing the number of sources of randomness greatly increases model run times and breaks the direct mapping from macroeconomic scenarios to outcomes, thus reducing the clarity of story-telling.

—*Stress testing:* RAMSI will be of particular use in providing model-based estimates of the impact of the risks highlighted in the Bank of England's Financial Stability Report (FSR). It will also be useful for running stress tests on the stability of the banking system under different stress scenarios. Relative to traditional stress tests, RAMSI integrates more of the channels through which shocks could propagate and takes account of the contagion that may occur through interbank exposures, asset fire sales, funding liquidity, and macroeconomic feedbacks. Assessment of the second-round effects has been identified by Haldane (2009) as an important area for development of stress testing in the financial system.

—*Assessing sources of risk to banks:* RAMSI will provide the relative contributions to overall risk of the various modules (credit

22. RAMSI's outputs may be used to provide alternative metrics of financial stability by recalibrating the reinvestment rule. To gauge declines in credit supply, it would be necessary to specify a reinvestment rule in which banks respond to losses by taking defensive actions, including reducing loans. Conversely, suppressing such mitigating actions would be a sensible option for assessing the potential for individual bank failures.

risk, market risk, funding risk, interest income risk, and other risks). In particular, RAMSI may be used to assess the contribution of systemic feedbacks to overall risk.

—*Intermediate outputs:* A number of RAMSI's outputs may be useful analytical tools, even when used in isolation from the rest of RAMSI. Examples include balance sheets, the credit loss model, the net interest income model, the ratings model, and the danger zone scores for funding liquidity crises.

—*Policy design:* RAMSI can be used for counterfactual experiments in which regulatory changes could affect systemic risk.[23] For example, we could analyze regulations that require banks to hold more capital or liquid assets or to vary their holdings across the cycle. The impact on risk and profitability can be observed on either a bank-by-bank or an aggregate basis. The modular approach also affords the possibility of measuring the potential benefits of diversification for each bank.

—*Recapitalization:* RAMSI could be used to calibrate the extent to which the recent recapitalization of the U.K. banking system reduces systemic risk.

4. Conclusion and Further Work

This paper incorporates funding liquidity risk into a quantitative model of systemic stability. By applying the model to the U.K. banking system based on the balance sheet vulnerabilities that existed at the end of 2007, we demonstrate how rising funding costs and liquidity concerns can amplify other sources of risk. The unified modeling approach sheds light on risks arising throughout banks' balance sheets. It also demonstrates how defaulting financial institutions may cause contagion by triggering default cascades through the interbank market; the sale of assets at fire-sale prices; and through the erosion of confidence in other banks.

We intend to develop the model in a number of areas. A substantial area for further work is to analyze banks' cash flow constraints and consider how defensive actions in the face of funding

23. See, for example, Goodhart (2008). Procyclicality will, to some extent, be built into the baseline of RAMSI when we introduce Basel II dynamic risk weights, which adjust to changes in the probability of defaults. In addition to the regulatory experiments above, RAMSI can allow for the possibility of procyclicality in terms of profits being reinvested in the most profitable (and risky) parts of the balance sheet.

stress may affect the rest of the financial system and the wider macroeconomy. In principle, macroeconomic feedbacks could be introduced by linking the realized banking-sector lending response to the price and quantity of loans in the BVAR, though we need to do more work to determine a coherent framework for embedding this important transmission channel. A further area for development will be to introduce more sources of randomness in the model beyond the BVAR (for example, in PDs). Such developments would clearly add to the computational complexity of RAMSI, but they would improve the realism of the various fan chart summaries of outcomes.

RAMSI has been one of the largest analytical projects at the Bank of England, and it will go live in 2009. Ultimately, its future development will largely be determined by the aspects of RAMSI that the Bank of England finds most useful in enhancing its understanding and communication of financial vulnerabilities. Our hope is that the analytical framework RAMSI provides will become central to the analysis of systemic risk in the United Kingdom and perhaps in other countries, as well.

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A Network Model of Super-Systemic Crises

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Are financial systems shock absorbers or shock amplifiers? Policymakers and academics have long remained divided over this fundamental question. On the one hand, some contend that financial innovation and integration make the financial world a safer place (Greenspan, 1999); others argue the opposite by appealing to the same driving forces (Rajan, 2005). The rapid financial innovation of the past several years has acted as both good and bad cholesterol—serving to lower the probability of crisis, but fattening the tail of the distribution of losses for the financial system as a whole (Gieve, 2006; Gai and Haldane, 2007). Although advanced country financial systems have withstood numerous shocks in recent years (the collapse of Amaranth, the events surrounding General Motors, 9/11, and the Dotcom crash, to name a few), the events triggered by the subprime crisis of August 2007 have been "super-systemic" in scope, enveloping financial institutions across the major economies as well as faraway Iceland and New Zealand.[1]

The intricate network of claims and obligations that now link the balance sheets of financial intermediaries raises challenges for the positive analysis of contagion in the modern financial system. In a

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1. We owe the term super-systemic to Andy Haldane.

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seminal analysis, Allen and Gale (2000) demonstrate how the spread of contagion depends crucially on the pattern of interconnectedness between banks. When the network is complete, with all banks having exposures to each other such that the amount of interbank deposits held by any bank is evenly spread over all other banks, the impact of a shock is readily attenuated. By contrast, the system is more fragile when the network is incomplete, with banks only having exposures to a few counterparties. The initial impact of a shock is concentrated among neighboring banks. Once these succumb, the premature liquidation of long-term assets and the associated loss of value bring previously unaffected banks into the front line of contagion.[2]

The financial turmoil of 2007–09 has also made clear how the interdependent nature of financial balance sheets creates an environment for indirect contagion to occur. As Cifuentes, Ferrucci, and Shin (2005), Shin (2008), and Brunnermeier and Pederson (2009) stress, the knock-on effect of the default of a financial institution on asset prices can trigger further rounds of default as other financial entities are forced to write down the value of their assets. In practice, technical default is not necessary for this effect to be relevant, as recent events highlight. Contagion from direct interlinkages of claims and obligations may thus be reinforced, particularly if the market for key financial assets is illiquid.

Given the speed with which shocks propagate, there is a need to develop tools that permit economists to articulate the probability and impact of shocks to the financial system. The complexity of modern financial systems means that policymakers have scant information about the true interlinkages between financial intermediaries. Securitization, for example, means that U.S. mortgage-backed securities acquired by investors in New Zealand or India expose households in these countries to credit events in Ohio. Information on such linkages is typically not in the public domain. Moreover, the intricacy of financial transactions has been such that private sector agents are also often no longer able to ascertain their own or others' exposure to credit risk. In this context, models such as Allen and Gale (2000), which are based on rigid structures with a handful of banks, have limited appeal. More recent literature on

2. See Freixas, Parigi, and Rochet (2000) for similar results. Network models have also been applied to a range of other topics in finance; for a comprehensive survey, see Allen and Babus (2009).

endogenous network formation (such as Leitner, 2005; Castiglionesi and Navarro, 2007) also fails to offer a framework that allows for arbitrary network structures or for a distinction between the probability and spread of contagion.

In this paper, we develop a network model of financial contagion that builds on techniques from the literature on complex systems (Strogatz, 2001). Although this type of approach is frequently applied to the study of epidemiology and ecology, and despite the obvious parallels between financial systems and ecosystems highlighted by prominent authors (such as May, Levin, and Sugihara, 2008), this methodology has yet to be applied to economic problems. Our model allows for arbitrary network structure and explicitly accounts for the nature and scale of aggregate and idiosyncratic shocks, as well as asset price interactions. Although the model can be solved analytically under certain assumptions, we present numerical results to illustrate and clarify the nonlinear system dynamics of the model.[3] In so doing, we are able to isolate the probability of contagion in the financial system from its potential spread.

We find that financial systems exhibit a robust-yet-fragile tendency. While greater connectivity reduces the likelihood of contagion, the impact on the financial system, should problems occur, could be on a significantly larger scale than before. Our results thus nest the two views of financial systems as shock absorbers versus amplifiers. The wider and deeper is financial innovation and integration, the more likely that the financial system serves as a shock absorber by enabling risk sharing. But innovation also has a dark side and can lead risk sharing to become risk spreading. So, although the incidence of acute financial distress may have fallen with greater financial interconnectedness, episodes of distress could have greater impact.

The rescue of American International Group (AIG) serves to illustrate the type of analysis made possible by our framework. A key reason given by policymakers for the rescue was concern that banks across the international financial system might have been exposed to AIG via credit derivative contracts. But how far could contagion have spread had AIG been allowed to fail? More generally,

3. Gai and Kapadia (2010) provide details of the analytical solution, applying techniques used in percolation theory (Callaway and others, 2000; Newman, Strogatz, and Watts, 2001; Watts, 2002) and in the epidemiological literature on the spread of disease in networks (for example, Newman, 2002; Meyers, 2007).

how might the expansion of credit risk transfer over the past decade have affected the nature of contagion? Given the limited information that policymakers have about the true interlinkages involved, the connections implied by credit derivatives are, perhaps, best captured by a random graph network of the type we consider here. Our results suggest that under plausible parameter values, greater use of credit derivatives might have reduced the likelihood of contagion. At the same time, by creating complex and far-reaching interlinkages in the financial system, their increased use could cause contagion to be transmitted much more widely.

A natural criticism of our framework is that it assumes that financial connections between intermediaries are formed randomly and exogenously and are static in nature. This leads us to model the contagion process in a relatively mechanical fashion, holding balance sheets and the size and structure of interbank linkages constant as default propagates through the system. Although not cast in a traditional optimizing setup, our approach does yield a useful and realistic benchmark for analysis. Arguably, in normal times, developed country banks are robust, and minor variations in their default probabilities do not affect lending decisions on the interbank market. In crises, however, as illustrated by the sudden failures of Bear Stearns and Lehman Brothers, contagion may spread rapidly, with banks having little time to alter their behavior before they are affected. Note also that banks have no choice over whether to default. This precludes strategic behavior on networks of the type discussed by Morris (2000), Jackson and Yariv (2007), and Galeotti and Goyal (2007), where nodes can choose whether to adopt a particular state (such as adopting a new technology).

Our paper is related to a large empirical literature that uses counterfactual simulations to assess the danger of contagion in a range of national banking systems (see Upper, 2007, for a comprehensive survey). This literature has largely tended to use actual or estimated data on interbank lending to simulate the effects of the failure of an individual bank on financial stability.[4] The evidence of contagion risk from idiosyncratic shocks is mixed. Furfine (2003) and Wells (2004) report relatively limited scope for contagion in the U.S. and U.K. banking systems. By contrast, Upper

4. A parallel literature explores contagion risk in payment systems; see, for example, Angelini, Maresca, and Russo (1996).

and Worms (2004) and van Lelyveld and Liedorp (2006) suggest that contagion risk may be somewhat higher in Germany and the Netherlands. Mistrulli's (2007) results for the Italian banking system echo the findings of this paper: he finds that while relatively small fraction of banks can trigger contagion, large parts of the system are affected in worst-case scenarios. Moreover, he shows that when moving from an analysis of actual bilateral exposures (which form an incomplete network) to a complete structure estimated using maximum entropy techniques, the probability of contagion from a random, idiosyncratic bank failure is reduced, but its spread is sometimes widened.

Contagion from aggregate shocks is examined by Elsinger, Lehar, and Summer (2006), who combine a model of interbank lending in the Austrian banking system with models of market and credit risk. They take draws from a distribution of risk factors and compute the effects on banks' solvency, calculating the probability and the severity of contagion. Their findings also echo the results reported here. While contagious failures are relatively rare, if contagion does occur, it affects a large part of the banking system.

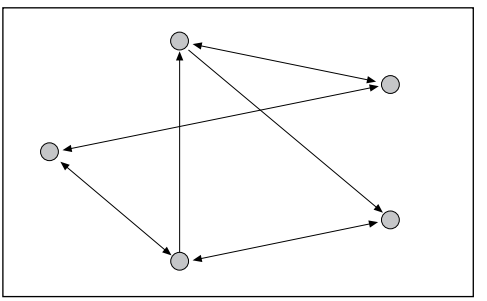
As noted by Upper (2007), existing empirical studies are plagued by data problems, and the extent to which reported interbank exposures reflect true linkages is unclear: generally, interbank exposures are only reported on a particular day once a quarter and exclude a range of items, including intraday exposures. They therefore underestimate the true scale of financial connectivity. Moreover, national supervisory authorities do not generally receive information on the exposures of foreign banks to domestic institutions, which makes it difficult to model the risk of global contagion in the increasingly international financial system. All of this, coupled with short time series for the relevant data, complicates the empirical assessment of the effects of changes in network structure, as perhaps induced by credit risk transfer, on contagion risk. This highlights the importance of analytical and simulation-based approaches to explore these issues.

The structure of the paper is as follows. Section 1 describes the analytical framework. Section 2 uses numerical simulations to study the effects of failures of individual institutions and articulate the likelihood and extent of contagion. It also considers the impact of liquidity effects and credit derivatives on system stability. A final section concludes.

1. Analytical Framework

Consider a financial network in which n financial intermediaries, (banks for short) are randomly linked together by their claims on each other. In the language of graph theory, each bank represents a node on the graph, and the interbank exposures of bank i define the links with other banks. Since interbank linkages comprise assets as well as liabilities, the links in the network are directed: incoming links, which point into a node or bank, correspond to the interbank assets or exposures of that bank (that is, the money owed to that bank by a counterparty); by contrast, outgoing links, which point out from a node, correspond to its interbank liabilities. Figure 1 shows an example of a directed financial network in which there are five banks.

Figure 1. A Directed Network with Five Nodes



Source: Authors' drawing.

Two crucial properties of graphs such as those in figure 1 are their degree distribution and average degree. Let us denote the number of incoming links, or in-degree, to bank i by j_i, and the number of outgoing links, or out-degree, by k_i. We can then define the joint degree distribution of in- and out-degree, p_{jk}, to be the probability that a randomly chosen node simultaneously has in-degree j and out-degree k. Further, since every interbank asset of a bank is an interbank liability of another, every outgoing link for one node is an incoming link for another node. Therefore, the average in-degree in the network,

$$\frac{1}{n}\sum_i j_i = \sum_{j,k} j p_{jk},$$

must equal the average out-degree,

$$\frac{1}{n}\sum_i k_i = \sum_{j,k} k p_{jk}.$$

We refer to this quantity as the average degree and denote it by

$$z = \sum_{j,k} j p_{jk} = \sum_{j,k} k p_{jk}. \tag{1}$$

In what follows, the joint distribution of in- and out-degree governs the potential for the spread of shocks through the network. A feature of our analysis is that this joint degree distribution, and hence the structure of the links in the network, is entirely arbitrary, though a specific distributional assumption is made in our numerical simulations.

Suppose that the total assets of each bank are normalized to unity and that these consist of interbank assets, A_i^{IB}, and illiquid external retail assets, such as mortgages and corporate loans, A_i^R. Since we might expect a bank with more incoming links to have a greater total interbank asset position, we allow for the relative shares of interbank and retail assets to depend on the bank's in-degree, j_i. Given these assumptions,

$$A_i^{IB}(j_i) + A_i^R(j_i) = 1\% \ \forall \ i, \tag{2}$$

where $A_i^{IB}(0) = 0$.[5] We assume that the total interbank asset position of every bank is evenly distributed over each of its incoming links. Although this assumption is stylized, it provides a useful benchmark that emphasizes the possible benefits of diversification.

Since every interbank asset is another bank's liability, interbank liabilities, L_i^{IB}, are endogenously determined. Apart from interbank liabilities, the only other component of a bank's liabilities are exogenously given customer deposits, D_i. The condition for bank i to be solvent is therefore

$$(1-\lambda\phi)A_i^{IB}(j_i) + qA_i^R(j_i) - L_i^{IB} - D_i > 0, \tag{3}$$

5. Across the entire financial system, we might expect total retail assets to be fixed. This would imply a dependence between the average share of retail assets on bank balance sheets and the number of financial intermediaries in the system. As discussed below, our numerical simulations take this dependency into account.

where ϕ is the fraction of banks with obligations to bank i that have defaulted, λ is the average loss-given-default on interbank loans, and q is the resale price of the illiquid asset. The value of λ is constrained to lie between zero and one: $\lambda = 1$ corresponds to a zero recovery assumption, namely, that when a linked bank defaults, bank i loses all of its interbank assets held against that bank. The value of q may be less than one in the event of asset sales by banks in default, but it equals one if there are no fire sales. The solvency condition can also be expressed as

$$\phi < \frac{K_i - (1-q)A_i^R(j_i)}{\lambda A_i^{IB}(j_i)}, \text{ for } \lambda A_i^{IB}(j_i) \neq 0, \tag{4}$$

where $K_i = A_i^{IB}(j_i) + A_i^R(j_i) - L_i^{IB} - D_i$ is the bank's capital buffer, that is, the difference between the book value of its assets and liabilities.

To model the dynamics of contagion, we suppose that all banks in the network are initially solvent and that the network is perturbed at time $t = 1$ by the initial default of a single bank. Although purely idiosyncratic shocks are rare, the crystallization of operational risk (for example, fraud) has led to the failure of financial institutions in the past (as in the case of Barings). Alternatively, bank failure may result from an aggregate shock that has particularly adverse consequences for one institution: this can be captured in the model through a general erosion in the stock of retail assets or, equivalently, capital buffers across all banks, combined with a major loss for one particular institution.

Recall that j_i denotes the number of incoming links for bank i. Since linked banks each lose a fraction $1/j_i$ of their interbank assets when a single counterparty defaults, it is clear from equation (4) that the only way default can spread is if there is a neighboring bank for which

$$\frac{K_i - (1-q)A_i^R(j_i)}{\lambda A_i^{IB}(j_i)} < \frac{1}{j_i}. \tag{5}$$

We define banks that are exposed in this sense to the default of a single neighbor as vulnerable and other banks as safe. The vulnerability of a bank clearly depends on its in-degree, j. Specifically, a bank with in-degree j is vulnerable with probability

$$\upsilon_j = P\left[\frac{K_i - (1-q)A_i^R(j_i)}{\lambda A_i^{IB}(j_i)} < \frac{1}{j_i}\right] \quad \forall\, j_i \geq 1. \tag{6}$$

Further, the probability of a bank having in-degree j and out-degree k and being vulnerable is $\upsilon_j \cdot p_{jk}$.

The model structure described by equations (2) to (6) captures several features of interest in systemic risk analysis. First, as noted above, the nature and scale of adverse aggregate or macroeconomic events can be interpreted as a negative shock to the stock of retail assets, A_i^R, or, equivalently, to the capital buffer, K_i. Second, idiosyncratic shocks can be modeled by assuming the exogenous default of a bank. Third, the structural characteristics of the financial system are described by the distribution of interbank linkages, p_{jk}, and much can be learned about the nature of contagion by simply exploring the effects of varying the average degree in the network, z. Fourth, the implications of different dependencies between the total interbank asset position and the number of exposures can be explored by changing the functional form of $A_i^{IB}(j_i)$. Finally, liquidity effects associated with the potential knock-on effects of default on asset prices are captured by allowing q to vary.

In Gai and Kapadia (2010), we use probability-generating function techniques to obtain analytical results on the transmission of shocks in the system as a function of v_j and p_{jk} in the special case in which the total interbank asset position is independent of the number of the bank's incoming links—that is, $A_i^{IB}(j_i)$ is constant and does not depend on j_i—and both λ and q are set equal to one. That paper shows that under these assumptions, financial systems exhibit a robust-yet-fragile tendency. While greater connectivity reduces the likelihood of contagion, its potential spread could be significantly greater should problems occur.

The intuition underpinning these results is straightforward. In a more connected system, the counterparty losses of a failing institution can be more widely dispersed to, and absorbed by, other entities. Increased connectivity and risk sharing may thus lower the probability of contagion. However, conditional on the failure of one institution triggering contagious defaults, a higher number of financial linkages also increases the potential for contagion to spread more widely. In particular, greater connectivity increases the chances that the institutions that survive the effects of the initial default will be exposed to more than one defaulting counterparty

after the first round of contagion, making them vulnerable to a second-round default. The impact of any crisis that does occur could therefore be larger.

In Gai and Kapadia (2010), we discuss how assuming an uneven distribution of interbank assets over incoming links would not change any of their fundamental results. The effects of the other simplifying assumptions required to obtain an analytical solution are less clear. In particular, that paper does not explore the implications of making the total interbank asset position dependent on the number of exposures, making it difficult to assess, for example, the effects of more widespread use of credit derivatives. Therefore, in what follows, we use numerical simulations to explore the implications of relaxing some of the simplifying assumptions needed to solve the model analytically.

2. Numerical Simulations

In our numerical simulations, we assume a uniform (Poisson) random graph in which each possible directed link in the graph is present with independent probability p. In other words, the network is constructed by looping over all possible directed links and choosing each one to be present with probability p. Consistent with bankruptcy law, we do not net interbank positions, so it is possible for two banks to be linked with each other in both directions. The average degree, z, is allowed to vary in each simulation. Although our model applies to networks of fully heterogeneous financial intermediaries, we take the capital buffers and asset positions on banks' balance sheets to be identical.

As a benchmark, we consider a network of 1,000 banks. Clearly, the number of financial intermediaries in a system depends on how the system is defined and what counts as a financial intermediary. However, several countries have banking networks of this size, and a figure of 1,000 intermediaries also seems reasonable if we are considering a global financial system involving investment banks, hedge funds, and other players. Given this rather high number of banks, when calculating the probability and conditional spread of contagion, we only count episodes in which over 5 percent of the system defaults, as this seems a suitable lower bound for defining a systemic financial crisis in such a large system. When assessing the impact of credit risk transfer, we change these assumptions to reflect the smaller number of major players in credit derivative markets and their greater systemic importance.

Except for the credit derivative experiment, interbank assets are assumed not to depend on the number of incoming links and are held constant at 20 percent of total assets, with retail assets making up the rest.[6] Banks' capital buffers are set at 4 percent, a figure calibrated from data contained in the 2005 published accounts of a range of large, international financial institutions.[7] Since each bank's interbank assets are evenly distributed over its incoming links, interbank liabilities are determined endogenously within the network structure. The liability side of the balance sheet is topped up by customer deposits until the total liability position equals the total asset position.

In the experiments that follow, we draw 1,000 realizations of the network for each value of z used. In each of these draws, we shock one bank at random, wiping out all of its external assets—this type of idiosyncratic shock may be interpreted as a fraud shock. The failed bank defaults on all of its interbank liabilities. As a result, neighboring banks may also default if their capital buffer is insufficient to cover their loss on interbank assets. Any neighboring banks that fail are also assumed to default on all of their interbank liabilities, and the iterative process continues until no new banks are pushed into default.

2.1 Benchmark Case

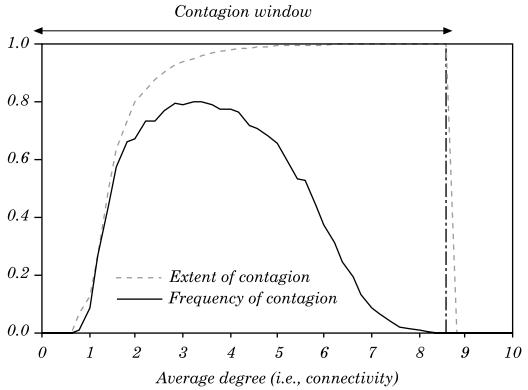
As a benchmark, figure 2 depicts the numerical solution under the assumptions needed to solve the model analytically. With no links, contagion is impossible by definition. Therefore, for very low values of z, the likelihood of contagion is increasing in connectivity.

More interesting is what happens for higher values of z. The frequency of contagion gradually falls as risk-sharing effects serve to reduce the number of vulnerable banks in the system. When contagion does break out, however, it affects an increasing fraction of the system. Indeed, for $z > 8$, contagion never occurs more than five times in 1,000 draws, but in each case where it does break out, every bank in the network fails. In addition to pointing toward the robust-yet-fragile nature of financial networks, this serves to highlight that a priori indistinguishable shocks to the network can

6. The 20 percent share of interbank assets is broadly consistent with the figures for developed countries reported by Upper (2007).

7. Further details are available on request.

Figure 2. Contagion in the Benchmark Case



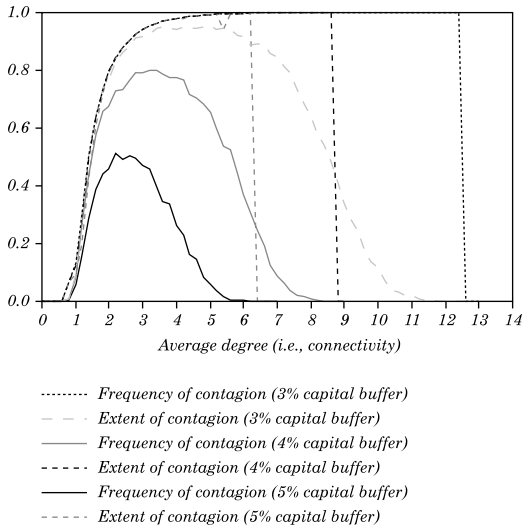
Source: Authors' calculations.

have vastly different consequences for contagion. In each draw, the initial shock is the failure of a single bank. In general, this does not cause contagion, but it is catastrophic in a small handful of cases. This feature of the complex network cautions against assuming that past resilience to a particular shock will continue to apply to future shocks of a similar magnitude. It also highlights the acute difficulties that policymakers may have when trying to assess the contagion risk from the failure of an institution if they do not have a good understanding of the structure of the financial network.

Figure 3 shows how the results change as banks' capital buffers vary. As might be expected, an erosion of capital buffers increases the probability of contagion for fixed values of z.[8] For small values of z, the extent of contagion is also slightly greater when capital buffers are lower but, in all cases, it reaches one for sufficiently high values of z. When the capital buffer is increased to 5 percent, however, this occurs well after the peak probability of contagion. This neatly illustrates how increased connectivity can simultaneously reduce the probability of contagion and increase its spread when it does break out.

8. Reduced capital buffers may also increase the likelihood of an initial default. Therefore, they may contribute to an increased probability of contagion from this perspective, as well.

Figure 3. Contagion under Different Capital Buffers



Source: Authors' calculations.

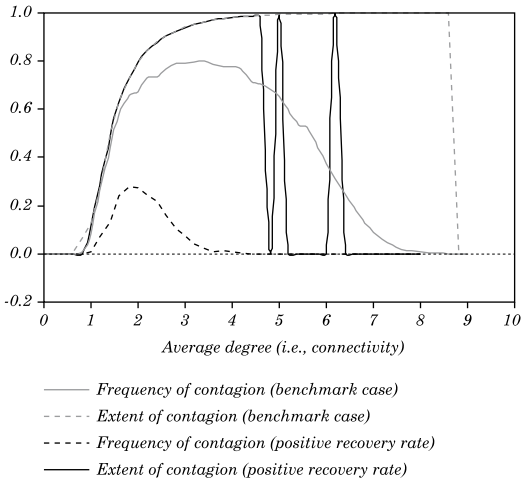
2.2 Positive Recovery Rates

Solving the model analytically requires assuming a 100 percent loss given default on interbank assets. This assumption may well be realistic in the midst of a crisis: in the immediate aftermath of a default, the recovery rate and the timing of recovery will be highly uncertain, and banks' funders are likely to assume the worst-case scenario. To assess the robustness of the results, we relax the zero recovery assumption and assume that when a bank fails, its default in the interbank market equals its asset shortfall (that is, its outstanding loss after its capital buffer is absorbed) plus half of any remaining interbank liabilities, where the additional amount is interpreted as reflecting bankruptcy costs that are lost outside the system (see figure 4).[9] As we might expect from equation (6), this reduces the likelihood

9. Since interbank assets make up 20 percent of each bank's total asset position, interbank liabilities must, on average, make up 20 percent of total liabilities. Therefore, if we take (insured) customer deposits as senior, the maximum bankruptcy cost for the average bank under this assumption is 10 percent of total assets or liabilities, which accords with the empirical estimates of bankruptcy costs in the banking sector reported by James (1991).

of contagion because fewer banks are vulnerable when the recovery rate is positive. This exercise illustrates that relaxing the zero recovery assumption does not fundamentally affect our broad results.

Figure 4. Contagion with Positive Recovery Rates



Source: Authors' calculations.

2.3 Liquidity Risk

We now incorporate liquidity effects into our analysis. When a bank fails, financial markets may have a limited capacity to absorb the illiquid external assets that are sold. As a result, the asset price may be depressed. Following Schnabel and Shin (2004) and Cifuentes, Ferrucci, and Shin (2005), we assume that the price of the illiquid asset, q, is given by

$$q = e^{-ax}, \tag{7}$$

where $x > 0$ is the fraction of system (illiquid) assets that have been sold onto the market (if assets are not being sold onto the market, then $q = 1$). We calibrate α so that the asset price falls by 10 percent when one-tenth of system assets have been sold.

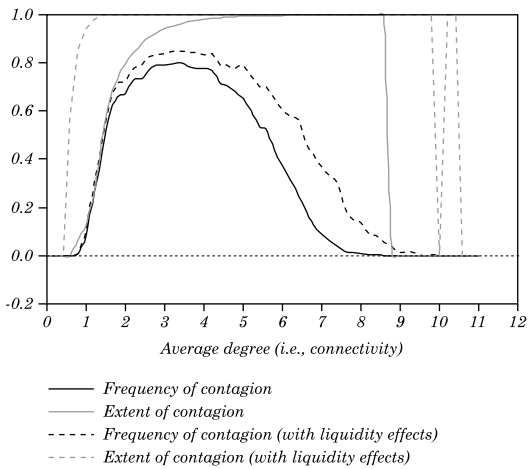
We integrate this pricing equation into our numerical simulations. Specifically, when a bank defaults, all of its external assets are sold

onto the market, reducing the asset price according to equation (7). We assume that when the asset price falls, the external assets of all other banks are marked to market to reflect the new asset price. From equation (6), it is clear that this will reduce banks' capital buffers and has the potential to make some banks vulnerable, possibly tipping them into default.

The incorporation of (market) liquidity risk introduces a second potential source of contagion into the model from the asset-side of banks' balance sheets. Liquidity risk only materializes upon default, however. Realistically, asset prices are likely to be depressed by asset sales before any bank defaults, so accounting only for the post-default impact probably understates the true effects of liquidity risk.

Figure 5 illustrates the effects of incorporating liquidity risk into the model. As we might expect, liquidity effects magnify the extent of contagion when it breaks out. Contagion is also slightly more likely for given values of z.

Figure 5. Liquidity Effects and Contagion



Source: Authors' calculations.

As shown, liquidity effects do not drastically alter the main results of our model, but this should not be taken to mean that liquidity effects are unimportant. In part, the limited effect of liquidity risk reflects the already high spread of contagion embedded in the benchmark scenario. If a fraction of banks were assumed to

be totally immune to counterparty credit risk (that is, they would survive even if all their counterparties defaulted), then liquidity risk would probably be much more significant in amplifying the extent of contagion for intermediate levels of connectivity. To the extent that liquidity risk materializes before any bank defaults, it can be viewed as having the potential to erode capital buffers and increase the likelihood of an initial default.

2.4 The Impact of Credit Derivatives

We now illustrate the type of analysis made possible by our framework by using it to assess the possible impact of credit derivatives on the nature of contagion. The use of credit derivatives has grown tremendously in recent years. For the net buyers of credit protection (typically traditional banks), this has reduced their exposure to nonfinancial corporates. At the same time, it has increased both their number of links to financial counterparties and their overall exposure to them. Meanwhile, net sellers of credit protection (such as insurance companies and monolines) have implicitly taken on corporate credit risk and become part of the financial network through their activities. For the system as a whole, the greater use of credit risk transfer may have slightly reduced capital buffers.

To capture these features in our model, we assume that the greater use of credit derivatives increases the number of incoming links for a typical bank and correspondingly expands the share of interbank assets on its balance sheet. Specifically, we assume the following functional form for $A_i^{IB}(j_i)$:

$$A_i^{IB}(j_i) = aj_i^b + c, \tag{8}$$

where $a > 0$ and $b > 0$ are parameters controlling the extent to which the total interbank exposure increases with the number of incoming links.[10] We also assume that the total stock of retail assets in the economy has remained constant. Together, these assumptions imply that the number of institutions in the network must have increased, which we associate with the integration of insurance companies,

10. Intuitively, introducing this relationship curtails the risk-sharing benefits of greater connectivity because the greater absolute exposure associated with a higher number of links partially offsets the positive effects from greater diversification.

hedge funds, and monolines into the system. To capture the possible erosion of capital buffers, we suppose that the total capital in the system remains unchanged despite the increase in the number of participants. As a result, all institutions become slightly less well capitalized as credit derivatives assume a greater role. All of these effects automatically key off an increase in the average degree, z.

Since our focus is on the relatively limited set of key players in global credit derivative markets, we suppose that in the initial state before the advent of credit derivatives, there were only 100 banks, with each having a 4 percent capital buffer and just two interbank links, on average. We then simulate the system for different values of z, assuming that $a = 0.02$, $b = 0.85$, and $c = 0.03$, that the loss given default on interbank exposures is 100 percent, and that there are no liquidity effects. Given that the typical bank currently has an interbank asset share of approximately 20 percent (Upper, 2007), this parameterization generates reasonably plausible interbank asset shares for the corresponding number of links (see table 1, column 2). For example, if a bank is linked to one-fifth of the system ($z = 20$), interbank assets constitute 28.5 percent of its balance sheet.

Table 1. Credit Derivative Simulation

Average degree (z)	*Interbank assets (%)*	*Retail assets (%)*	*No. of banks*	*Capital buffer (%)*	*Frequency of contagion (%)*	*Scale of contagion (%)*
2	6.6	93.4	100	4.00	7.8	3.8
5	10.9	89.1	105	3.82	6.2	5.4
10	17.2	82.8	113	3.55	2.1	35.4
15	23.0	77.0	121	3.30	0.9	67.8
20	28.5	71.5	131	3.06	0.9	89.1
25	33.9	66.1	141	2.83	0.2	100.0

Source: Authors' calculations.

Table 1 shows how the probability and spread of contagion vary with z. Given our focus on major international financial institutions in this analysis, we adopt a lower threshold for recording contagion events, counting all episodes in which more than one bank defaults as a result of the initial failure. It is evident from the table that the greater use of credit derivatives, as captured by an increase in z, may have reduced the likelihood of contagion following an initial

failure. Moreover, to the extent that credit risk transfer may reduce the probability of an initial default, the results may understate its beneficial effects. Nevertheless, the role of credit derivatives as a potential shock amplifier is revealed by the sharply increasing spread of contagion. With an average of five links, contagion only affects roughly 5 percent of the system when it breaks out. An increase to ten or fifteen links changes the picture completely—once started, crises become super-systemic.

These results (and indeed all of the numerical results presented in the paper) are cast in terms of random graph network structures involving financial intermediaries (nodes) with comparable balance sheets. As such, our findings could underestimate the impact of an actual financial crisis. If the first bank to fail is particularly large or highly connected (such as Lehman Brothers), then the consequences could be much more severe. Albert, Jeong, and Barabasi (2000) study the effects of targeted attacks on hubs and show how critical nodes are vital to the spread of contagion.[11] The existence of a key node may also be beneficial, however. With clear analogies to the epidemiological literature on targeted vaccination of highly connected nodes (Anderson and May, 1991), if the authorities are able to identify and bail out key players in the network ex ante, then prospective contagion could be very substantially contained. Extensions of our analysis in these directions are likely to reach similar conclusions.

3. Conclusion

In this paper, we develop a model of contagion in arbitrary financial networks that nests the two competing views of financial systems as shock absorbers or amplifiers. In so doing, our framework helps clarify how shocks are transmitted across markets and banking systems. A key finding is that while greater connectivity helps lower the probability of contagion, it can also increase its spread in the event of problems occurring. Illiquid markets for key financial assets compound the problem, amplifying both the likelihood and extent of contagion.

Our model helps illustrate how the failure of a large organization linked to other entities via credit derivatives might play out in the absence of a public sector rescue. The use of credit derivatives in our

11. Nier and others (2007) also provide some analysis of shocks to key nodes in hub-and-spoke networks.

model creates far-reaching interlinkages and large absolute exposures compared with financial systems that lack such instruments. We demonstrate how the expansion of credit derivative activity may have worked to curtail some of the risk-sharing benefits offered by such innovation, leaving open the scope for a much more virulent or super-systemic crisis.

Finally, the paucity of relevant balance sheet data on many financial entities and the international nature of financial intermediation make the empirical modeling of contagion risk difficult to undertake. By isolating probability and impact, our paper also makes a methodological contribution, pointing toward analytical and numerical approaches for assessing the effects of changes in network structure on contagion risk.

Our paper is best viewed as a first step in a research agenda that seeks to develop a deeper understanding of large, complex financial networks. Clearly, there remains scope to sharpen the calibration that forms the basis of the main results. A more pressing challenge, however, is to relax some of the more mechanical assumptions of the analysis. Developing a more behavioral foundation in ways that capture the richness of financial network structure is a crucial next task if such models are to offer further meaningful guidance for policymakers.

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