CHAPTER 3

Summary

Operationalizing macroprudential policies requires progress on a number of fronts: developing ways to monitor a risk buildup, choosing indicators to detect when risks are about to materialize, and designing and using macroprudential policy tools. Establishing these robust frameworks will be a lengthy process. Using a structural model and empirical evidence, the following analysis takes a solid step forward on each of the interrelated tasks.

Detecting both the slow buildup and the sudden materialization in systemic risk is the key to implementing good macroprudential policies. These two phases require two different sets of indicators. Slow-moving leading indicators signal risks are building up in the financial system and propagating to the real economy through financial intermediaries. High-frequency market-based indicators predict an imminent unwinding of systemic risk and potentially provide information on the extent of interconnectedness of financial institutions and its possible consequences.

This chapter uses a structural model with financial and real sector linkages to help policymakers understand the underpinnings of a systemic risk buildup. Empirical exercises further test the capabilities of indicators to predict financial crises and alert policymakers to the need for action. After identifying the buildup in systemic risk, policymakers will inevitably want to consider policies best suited to address the problem. The chapter illustrates how a countercyclical capital requirement would operate—with the accumulation of capital when risks are building and a drawdown of this capital buffer when high-frequency indicators are flashing an imminent crisis—as well as how it can be successful in cushioning the economy's real output during a crisis.

The chapter provides a few practical guidelines for operationalizing macroprudential policies.

- Movements in indicators for systemic risk buildup vary with the underlying root causes. Distinguishing "good" shocks (such as expected productivity gains) from "bad" shocks (asset price bubbles and lax lending standards) is important if policymakers are to avoid using macroprudential policies to squash healthy economic growth inappropriately.
- Credit growth and asset price growth together form powerful signals of systemic risk buildup as early as two to four years in advance of crises. Other variables can also help.
- Initial comparative analyses of high-frequency indicators suggest that those using a combination of the LIBOR-OIS spread and the yield curve could signal an imminent crisis and put policymakers on alert to execute contingency plans.
- Macroprudential policy tools can be used across countries with different economic characteristics as long as policymakers understand the source of shocks. However, tools need to be calibrated more conservatively for managed exchange rate regimes that feature widespread lending denominated in foreign currencies because these characteristics tend to amplify the transmission mechanism of any shock.
- Macroprudential and monetary policymakers need to coordinate in at least two areas: understanding the basic source of shocks and their policies in managed exchange rate regimes with widespread foreign currency lending.

Macroprudential policy uses primarily prudential tools to limit systemic risk.[1] Hence, successful macroprudential policy implementation is contingent on establishing robust methods for detecting systemic risk and a set of policy tools designed to mitigate it. Since the 2007–09 financial crisis, new tools for monitoring systemic risk have mushroomed in the academic literature and within policy-making circles.[2] The IMF has also enhanced its surveillance tools in the context of its early warning exercise, including the methods for monitoring risks associated with the financial sector (IMF, 2010b). Yet, even as various countries have recently set up macroprudential policy frameworks, there is still no robust set of indicators for detecting systemic risk (Box 3.1). Nor is there much guidance, from a conceptual perspective, on which macroprudential policy tools to apply under specific circumstances, although some types of tools have been used before.

It is widely agreed that risks can build up in the financial system over time and materialize precipitously during a crisis (Drehmann, Borio, and Tsatsaronis, forthcoming). This observation suggests that slow-moving financial balance sheet aggregates should be complemented by fast-moving market-based indicators. Credit growth, as a low-frequency indicator, has been used for detecting risk buildup for some time now, but the idea has resurfaced in the wake of the global financial crisis.[3] This is especially so due to its ability to propagate and amplify shocks from the financial intermediaries to the real sector and vice versa. However, a broader spectrum of slow-moving macroeconomic and financial variables may do even better to inform policymakers of the buildup of systemic risk.

While less apt to aid in detecting buildup, fast-moving financial indicators can help predict impending risks, alerting policymakers that a crisis may be imminent (IMF, 2009). Additionally, some of these indicators can provide information on the extent of interconnectedness of financial institutions, which is crucial for policymakers to understand the transmission and amplification mechanism of a shock and activate contingency plans.

This chapter finds that understanding the source of a shock and how it is transmitted to the economy is key to identifying leading and near-coincident indicators for monitoring systemic risk, as well as the tools to mitigate it. For example, a crisis may result from the bursting of a real estate bubble—a shock that is reflected in credit and funding aggregates. These aggregates may behave differently in the face of nonsystemic shocks, such as productivity improvements.

This chapter aims to contribute to operationalizing macroprudential policies along two dimensions.[4] *First*, it investigates the usefulness of various techniques to identify indicators for the buildup and materialization of systemic risk. It takes a two-pronged approach to do so (Figure 3.1): it uses a structural model of macroeconomic–financial linkages to identify a set of indicators that would help identify the source of systemic risk; and, informed by the model, it uses statistical techniques to choose a robust set of systemic risk indicators. *Second,* it sheds some light on how policy instruments can be applied to mitigate the buildup of systemic risk. Establishing comprehensive macroprudential policy frameworks will take time, and the chapter's analysis should be viewed as "work in progress" in the quest to move forward. In this regard, key questions and new analytical insights pursued in the chapter include:

- How can one use a model of macroeconomic–financial interactions to identify meaningful early warning indicators for systemic financial risk? The

Note: This chapter was written by Srobona Mitra (team leader), Jaromír Beneš, Silvia Iorgova, Kasper Lund-Jensen, Christian Schmieder, and Tiago Severo. Research support was provided by Ivailo Arsov and Oksana Khadarina.

[1]Systemic risk is the risk of disruptions to financial services that is caused by an impairment of all or parts of the financial system, and can have serious negative consequences for the real economy (IMF-BIS-FSB, 2009; IMF, 2011b). Systemic risk is driven by economic and financial cycles over time, as well as by the degree of interconnectedness of financial institutions and markets.

[2]See discussions in IMF (2009, 2011a and 2011b); Adrian and Brunnermeier (2010); Acharya and others (2010); Billio and others (2010); BCBS (2010); and Brownlees and Engle (2011).

[3]For the precrisis literature, see Enoch and Ötker-Robe (2007) and references therein. Some recent studies include Mendoza and Terrones (2008); Barajas, Dell'Ariccia, and Levchenko (forthcoming); De Nicoló and Lucchetta (2010); Claessens, Kose, and Terrones (2011a and 2011b); Kannan, Rabanal, and Scott (2009a and 2009b); Borio and Drehmann (2009); Drehmann, Borio, and Tsatsaronis (forthcoming).

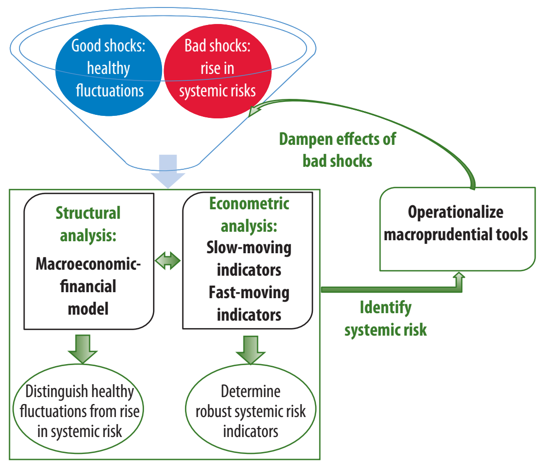
[4]The analysis builds on lessons from previous GFSR chapters (IMF, 2009 and 2011a) focusing on systemic risk issues.

chapter first lays out a structural model incorporating feedback between the banking sector and the real economy and shows how the interaction among several variables can allow policymakers to discern patterns of systemic risk buildup.

- How can empirical analysis help in identifying a set of robust indicators of systemic risk? The chapter evaluates both low- and high-frequency indicators based on their ability to make reasonably timely predictions about systemic stress. Such predictions allow policymakers to be adequately prepared to act.
- What are the considerations behind the design and effectiveness of macroprudential policy tools? The structural model introduced early in the chapter is used to examine how different sources of risk affect the use and effectiveness of countercyclical capital buffers, a key macroprudential policy tool. This discussion also sheds light on country practices.

Based on the above, in conclusion, the chapter proposes an initial, practical set of guidelines for monitoring systemic risk and operationalizing macroprudential policies.

Figure 3.1. Road Map of the Chapter



Box 3.1. Monitoring and Policy Tools at New U.S., U.K., and EU Macroprudential Authorities

The U.S. Financial Stability Oversight Council (FSOC)

- **Setup:** Established under the July 2010 Dodd-Frank Act, the FSOC is charged with identifying threats to financial stability, promoting market discipline, and responding to emerging risks to the stability of the U.S. financial system. It is chaired by the Treasury Secretary and brings together federal financial regulators, an insurance expert, and state regulators. By statute, the FSOC has a duty to facilitate the sharing of data and information among member agencies and to facilitate regulatory coordination. The FSOC will be based on a committee structure, with a Systemic Risk Committee; two subcommittees on institutions and markets, respectively; and several standing functional committees.
- **Monitoring:** The Systemic Risk Committee is responsible for identifying, analyzing, and monitoring risks to financial stability and for providing assessments of risks to the FSOC. The FSOC focuses on significant market developments, such as mortgage foreclosures in the United States and sovereign debt developments in Europe, as well as on structural issues, such as reform of the money market mutual fund industry. The FSOC is supported by the newly created Office of Financial Research (OFR), which is responsible for setting standards for data reporting and collecting while protecting confidential business data, and for analyzing risks to the financial system. The FSOC has the authority to direct the OFR to collect information from specific financial companies.
- **Policy Tools:** The FSOC has the authority to: (i) designate nonbank financial companies, regardless of their corporate form, for consolidated supervision; (ii) designate financial market utilities and payment, clearing, and settlement activities as systemic, requiring them to meet the risk management standards prescribed and be subject to heightened oversight by the Federal Reserve, the Securities and Exchange Commission, or the Commodity Futures Trading Commission; (iii) recommend stricter standards for the largest, most interconnected firms, including nonbanks, designated by the FSOC for Federal Reserve supervision; and for certain practices or

Note: Prepared by Ann-Margret Westin with contributions from Erlend Nier.

Box 3.1 *(continued)*

activities under the control of the primary financial regulatory agencies that are deemed to pose a threat to financial stability; (iv) recommend breaking up firms that pose a "grave threat" to financial stability; and (v) recommend that Congress close specific regulatory gaps.

- **Communication:** The FSOC meetings will be public whenever possible and held at least twice a year. The FSOC will report to Congress annually, and its chairperson will testify on its activities and on emerging threats to financial stability. The OFR will produce regular reports to Congress on significant market developments and potential emerging threats to financial stability.

The U.K. Financial Policy Committee (FPC)

- **Setup:** The FPC, which is expected to be established by end-2012, will be accountable to the governing body of the Bank of England (BoE). It will contribute to the BoE's financial stability objective by identifying, monitoring, and taking action to remove or reduce systemic risks.[1] Its focus will encompass structural aspects of the financial system and the distribution of risk within it, and cyclical threats from unsustainable levels of leverage, debt, or credit growth—with a view to protecting and enhancing the resilience of the U.K. financial system. The FPC must consider the potential for any adverse impact on medium- or long-term economic growth. An interim FPC was established in February 2011 and held its first official meeting in June. It will carry out preparatory work, including analysis of potential macroprudential tools, and monitor developments affecting financial stability in the United Kingdom and internationally. The interim FPC will advise the Financial Services Authority on emerging risks, including possible mitigating measures, and consider making recommendations to the Treasury about the regulatory perimeter.

[1]Until legislation establishing the FPC is passed, the BoE's Financial Stability Committee will continue with its statutory responsibilities in relation to the BoE's existing financial stability objective under the 2009 Banking Act.

- **Monitoring:** In monitoring financial stability, the FPC will identify emerging risks and vulnerabilities and cyclical imbalances using a broad range of indicators. The FPC will also monitor the activities of the prudential and other regulators, as well as the regulatory perimeter.
- **Policy Tools:** The FPC will be able to make recommendations on a "comply or explain" basis to the future Prudential Regulation Authority (PRA) and Financial Conduct Authority on their rules and policies. The FPC will also be able to direct the prudential regulators to take certain actions and must advise the government on changes in the perimeter of the PRA's prudential supervision. Instruments aimed at network issues could include recommendations or directions on disclosures regarding the issuance and structuring of securities; on the trading infrastructure of markets; on limits on large exposures among different kinds of firms; and on shadow banking rules. Cyclical instruments will include countercyclical capital buffers and might also include varying liquidity requirements, varying capital risk weights, and minimum haircuts for specific types of secured lending. Minimum margining requirements might also be applicable for key funding markets.
- **Communication:** The records of the interim FPC meetings are published, as will be those of the four regular meetings per year of the forthcoming FPC. A semiannual Financial Stability Report (FSR) will contain an assessment of risks to financial stability and action taken by the FPC and interim FPC. The publication of the FSR will coincide with an update by the Governor of the BoE to the Chancellor of the Exchequer.

The European Systemic Risk Board (ESRB)

- **Setup:** The ESRB, an independent EU body responsible for the macroprudential oversight of the financial system within the European Union, was established in December 2010, in line with the recommendations of the 2009 de Larosière Report. The ESRB contributes to the prevention or mitigation of systemic risks to financial stability in the EU. It also examines specific

Box 3.1 *(continued)*

issues at the invitation of the European Parliament, Council, or Commission. In pursuing its functions, the ESRB is required to coordinate closely with all the other parties in the European System of Financial Supervision as well as with the national macroprudential authorities across the EU. The ESRB held its inaugural meeting in January 2011 and its first of four regular annual meetings in March 2011. The president of the European Central Bank chairs the ESRB. Its General Board includes the governors of all EU central banks, the three new European regulatory authorities—the European Banking Authority, the European Securities and Markets Authority, and the European Insurance and Occupational Pensions Authority—and the European Commission; the national supervisory authorities are nonvoting members.

- **Monitoring:** In pursuing its function, the ESRB collects and analyzes all relevant and necessary information and identifies and prioritizes systemic risks. As appropriate, it provides the European Supervisory Authorities (ESAs) with the information on systemic risks required for the performance of their tasks. In particular, in collaboration with the ESAs, the ESRB will develop a common set of quantitative and qualitative indicators ("risk dashboard") to identify and measure systemic risk. The ESRB may also make specific requests for the ESAs to supply information on individual institutions.
- **Policy Tools:** The ESRB will not have direct control over policy instruments. Rather, it will issue warnings about significant systemic risks and, when appropriate, make those warnings public. It will also issue recommendations for remedial action in response to identified risks and, where appropriate, make those recommendations public. When the ESRB determines that an emergency situation may arise, it will issue a confidential warning to the European Council. The ESRB must monitor the response of agencies receiving its warnings and recommendations and ask those agencies for an accounting on an "act or explain" basis. Ensuring the effectiveness of the instruments will require the development of analytical tools and models that underpin the macroprudential policy process, including reliable systemic risk indicators that will support the issuance of warnings and inform its recommendations on the calibration of prudential measures.
- **Communication:** As noted above, the main instruments of the ESRB are warnings and recommendations that can be made public. Also, each ESRB meeting will be followed by a press release and/or press conference. Every year, the chair of the ESRB will be invited to a hearing in the European Parliament on the occasion of the ESRB's annual report to the Parliament and the Council.

Sources: www.bankofengland.co.uk/publications/news/2011/040.htm; www.bankofengland.co.uk/financialstability/fpc/termsofreference.pdf; www.ecb.europa.eu/press/key/date/2010/html/sp100929_1.en.html; www.esrb.europa.eu/home/html/index.en.html; www.hm-treasury.gov.uk/consult_financial_regulation.htm; www.hm-treasury.gov.uk/consult_finreg_strong.htm; www.treasury.gov/initiatives/Pages/FSOC-index.aspx; www.treasury.gov/initiatives/Pages/ofr.aspx; www.treasury.gov/press-center/press-releases/Pages/tg1139.aspx.

From Sources of Risk to Systemic Risk Indicators: Helpful Hints from a Structural Macro-Financial Model

Identifying leading indicators of crises requires a carefully specified structural model of the interactions between the financial sector and the real economy. Such a macro-financial model can show how changes in the sources of risk affect macroeconomic and financial variables. The model used here extends the traditional dynamic stochastic general equilibrium (DSGE) macroeconomic framework by taking into account the role of monetary and macroprudential policies, thus incorporating a more detailed interaction between the financial sector and the real economy (see Annex 3.1 for details).[5] Carefully specified structural models can provide useful insights by helping policymakers disentangle empirical relationships, think about various endogenous feedbacks between the real and the financial sectors, and impose a consistent structure on macroprudential policy.

The structural model could help predict movements of numerous macroeconomic and financial variables in response to alternative sources of shocks. For instance, rapid credit growth in a country is often associated with a higher probability of financial crisis.[6] But a boom in credit can also reflect a healthy response of markets to expected future productivity gains.[7] Indeed, many episodes of credit booms were not followed by a financial crisis or any other material instability. Policymakers should certainly use macroprudential instruments when credit booms threaten financial stability, but such instruments should not be used if they risk aborting a fundamentally solid expansion. To ensure that policies are appropriately designed and implemented, authorities need information that would allow them to distinguish between these different scenarios. The structural model should be able to inform policymakers of the variables that could be used for this purpose and how best to extract information on the sources of shocks.

Key features of the model used here are the inclusion of a realistic banking sector and a flexible set of parameters to mimic different types of economies (Beneš, Kumhof, and Vávra, 2010; and Annex 3.1). The innovative features of the banking part of the model are: (i) inclusion of the balance sheets of both banks and nonfinancial borrowers in the propagation of shocks; and (ii) a link between the diversifiable (or idiosyncratic) risk faced by banks in their lending activities and the nondiversifiable, aggregate macroeconomic risk arising from cyclical fluctuations.[8] The macroprudential concern stems from the presence of the aggregate risk. Examples of the flexible parameters are the extent of foreign-currency-denominated loans, the degree to which the central bank manages the nominal exchange rate, the sensitivities of both imports and exports to the exchange rate, and the ease with which banks can raise fresh equity capital in financial markets.

We use the model to address the following questions:

- Which variables are leading indicators of future financial instability?
- How do the leading indicators react to different types of shocks?
- Can the leading indicators differentiate healthy credit booms from unhealthy episodes of credit growth?

[5]The IMF and major central banks have developed one or more versions of these DSGE macroeconomic models to study the effectiveness and desirability of different macroeconomic policies (Roger and Vlćek, 2011 and forthcoming). More recently, DSGE models have also been used for forecasting purposes. For example, Smets and Wouters (2007) show an application of Bayesian techniques for the estimation of DSGE models that yields good forecasting properties.

[6]Bordo and others (2001), Reinhart and Rogoff (2009), and Mendoza and Terrones (2008) have compiled vast amounts of evidence about various drivers of boom-and-bust cycles across numerous countries over time. Moreover, Borio and Drehmann (2009), Drehmann, Borio, and Tsatsaronis (forthcoming), and Ng (2011) study the performance of alternative indicators of financial crisis; those studies show that some variables, including measures of excessive credit growth, could forecast crises occurring one to three years ahead. De Nicoló and Lucchetta (2010) explore the links between credit growth and GDP growth with a dynamic factor model using the concept of tail risk (the risk of negative shocks of low probability but high impact).

[7]Such gains could result from one or more developments, including new technologies, new resources, and institutional improvements.

[8]The model uses the concept of financial friction (see Bernanke, Gertler, and Gilchrist, 1999), in which limited enforcement of loan covenants gives the borrower an incentive to default and allows the lender to seize the collateral. The aggregate risk in the model arises from procyclicality in the system; the model does not take into account the systemic risk arising from interconnectedness in the financial system.

- Do the indicators vary according to characteristics of the economy, such as the degree of trade and financial openness or the nature of its exchange rate regime?

We consider three types of shocks, each of which can cause prolonged periods of rapid credit growth, persistent increases in the value of assets, and external imbalances.[9] The first two of the three shocks described below will likely increase systemic risk; the third represents a healthy change and does not expose the financial sector or the overall economy to substantial instabilities. In reality, all three shocks could (and often do) occur together. But the purpose of using the structural model is to be able to clearly distinguish between them so as to derive the implications for different indicators.

- The first shock is an *asset price bubble* (Bernanke and Gertler, 1999) that lasts for about 12 consecutive quarters.[10] The bubble is irrational because it is not underpinned by a change in fundamentals. It can be viewed as an exogenous persistent wedge between the price of certain assets and their fundamental level. While the bubble persists, credit risk builds up on the balance sheets of financial institutions—banks lend to households and businesses against financial wealth that is inflated by mispriced assets. When the bubble bursts, the credit risk materializes.
- The second shock is a *lowering of bank lending standards* for eight consecutive quarters. Banks seeking to increase their share in a highly competitive market may underestimate the true risk associated with lax lending standards.[11] Thus, the systemic risk in this scenario is generated from within the financial sector. It could reflect increased moral hazard (a stronger belief that the government will bail out banks), overoptimistic assumptions about credit risk, or greater financial integration.
- The third shock is *anticipated improvement in the economy's fundamentals*, such as a productivity gain expected from a future inflow of foreign direct investment. The anticipated improvement, if realized, will expand the economy's production frontier, export capacity, and real income. The actual improvement occurs after 12 consecutive quarters.[12] In this scenario, households and other nonfinancial agents start borrowing against their future income before the improvement materializes. Resulting increases in indebtedness and current account deficits may not lead to risks unless the expectations are overly optimistic; the risks fade away as the fundamental improvements materialize.

Is it possible to empirically distinguish between these three situations in which fast credit growth creates different levels or types of systemic risk? The dynamics of many macroeconomic and financial sector variables are qualitatively similar for the different sources of shocks (Figure 3.2).[13] The figure shows the paths of four variables when each of the three shocks hits the economy in quarter 1.[14] For example, the credit-to-GDP ratio increases initially as a response to any of the three shocks.

[9]No distinction is made between various types of assets—productive real capital, real estate, claims to investments, equity shares, and so on.

[10]The analysis assumes "irrational" bubbles—investors' and traders' sentiments and expectations are driven by extraneous or nonfundamental factors such as fads, fashions, rumors, and informational "noise," which can disrupt and destabilize asset markets and generate excessive volatility in asset prices (Kindleberger, 1989). A "rational" bubble, on the other hand, reflects the presence of self-fulfilling (rational) expectations about future increases in the asset price raising the possibility of deviation of the asset price from the fundamental value (Blanchard, 1979; Blanchard and Watson, 1982; Froot and Obstfeld, 1991; and Evans, 1991). In a rational bubble, stock price growth contains occasional corrections when investors realize the price is not increasing as expected, as opposed to diverging continually as in the "irrational" case.

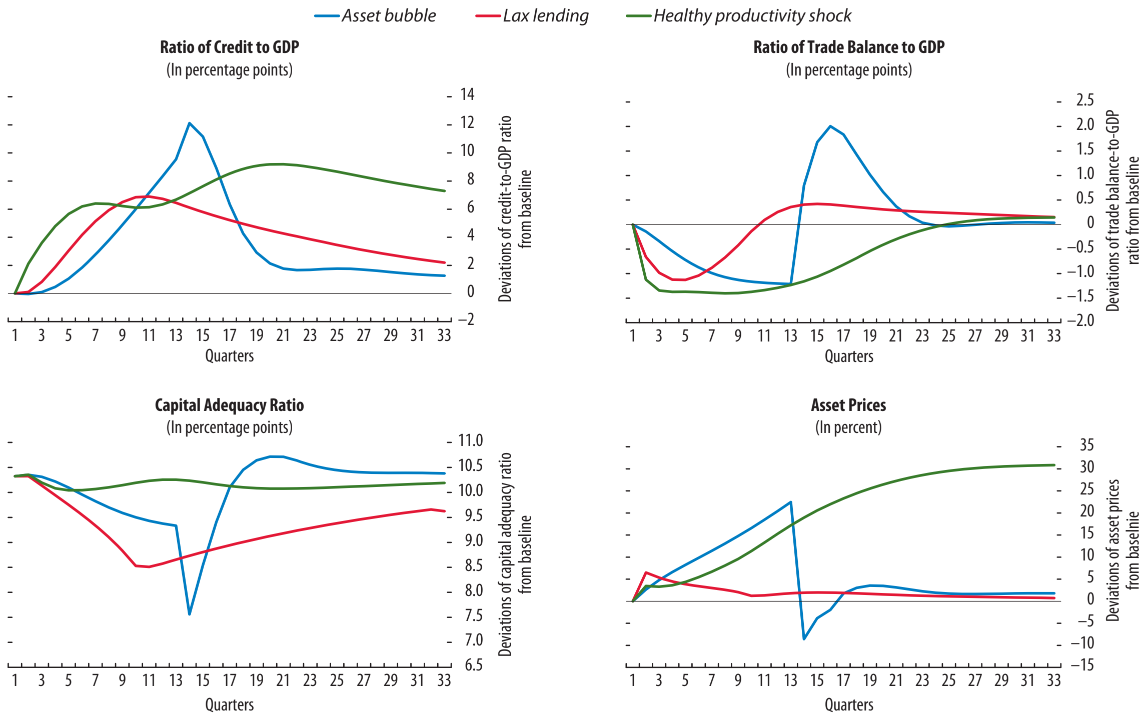
[11]Dell'Ariccia and Marquez (2006) show that, as more and more customers apply for bank loans, banks weaken their lending standards and collateral requirements to raise market share by undercutting their competitors.

[12]A bubble scenario could arise if the actual productivity gains are less than expected.

[13]Baseline parameterization drives the impulse responses that are used to construct Figure 3.2. Different parameterizations of the model are analyzed in Annex 3.1 and Beneš, Kumhof, and Vávra (2010). Impulse-response functions represent the deviations of macroeconomic variables from their regular path as a consequence of a disturbance, keeping all other elements constant. They compare the performance of the economy over time after a shock relative to a nonshock scenario. The length of the shocks is approximated using information about the time shocks tend to last in previous cases in a set of representative countries.

[14]Only four indicators have been shown in the figure for analytical purposes, but there are many other indicators that could be shown. Also see notes to Figure 3.2.

Figure 3.2. Behavior of Four Indicators under Three Shock Scenarios



Source: IMF staff estimates.

Note: For all three shock scenarios, the shock occurs in quarter 1. "Asset bubble" simulates a bubble in the price of productive capital (that is, the observed market price of capital differs systematically and persistently from the fundamental value) within the first 12 quarters and grows gradually to about 20 percent. After 12 quarters, the bubble bursts during the following three quarters. "Lax lending" simulates a loss-given-default that rises from an expected 20 percent to an actual 90 percent, and that returns only gradually to its original level. "Healthy productivity shock" is an expected improvement in productivity that actually materializes in two quarters.

This is indeed an important *first lesson* from the model:

- Increases in the credit-to-GDP ratio alone may signal undesirable speculative paths that risk derailing the financial sector and the economy, but they can also indicate a healthy cycle initiated by positive news about the future.

Despite the similarities among the variables, there are some important differences as well. Notably, the *second lesson* from the model is that even though the direction of change may be the same, the persistence (over several past quarters) and the degree of change in the key variables may not be. For example,

- The increase in the credit-to-GDP ratio from the baseline to the peak is about 12 percentage points in the case of an asset price bubble, whereas it is about half as much in the case of the productivity shock. When a shock arises from within the financial sector (lax lending standards), the credit-to-GDP ratio persistently increases until banks realize after some time that they were overestimating the credit quality of borrowers.
- The trade balance (in percent of GDP) immediately deteriorates under both lax lending standards and the productivity shock. The deterioration is sustainable only in the latter case as residents borrow against their (correctly anticipated) future productivity gains to purchase foreign goods and services. In contrast, under the lax lending standards scenario, the trade balance starts to improve when banks realize their mistake. In the case of the asset price bubble, the trade balance deteriorates much more gradually until it reverses sharply because of the asset price bust.
- The path of the bank capital adequacy ratio deteriorates substantially for the "perverse

shocks"—the asset price bubble and lax lending standards—but much less so upon positive news about productivity.

- The market price of capital (a measure of asset prices in the model) spikes quickly in response to the productivity shock and increases gradually afterward. In the case of the bubble, the increase is rapid before a sharp correction in response to the bust. Lax lending standards need not be accompanied by asset price increases although, in reality, they often are.
- Actual loan-to-value ratios (not shown in the figure) also behave differently.[15] It is almost unchanged in the initial stages of a bubble or following positive news about fundamentals. But it increases continuously when lending standards deteriorate, reverting slowly to its normal path as banks readjust their credit policies.[16]

Does the structure of the economy alter the second lesson? An important insight from the model is that the structural elements of the real economy, such as trade openness, do not make an appreciable difference in the relative movements in key variables following each shock. However, certain features of the *financial sector*—for instance, widespread foreign currency lending in a fixed or managed exchange rate regime—tend to magnify the effects of all shocks. This can be summarized as the *third lesson*:

- Sources of shocks matter more than some features of the real economy in driving movements in key indicators of systemic risk.
- Loans denominated in foreign currency, together with heavily managed exchange rates, tend to amplify the transmission mechanism of any shock.

In summary, the findings of this section are:

- All the responses to the shocks described above have distinctive patterns that are noticeable with enough lead time. For instance, increases in the credit-to-GDP ratio may signal the buildup of bubbles that wind up as future crises.
- Only when the ratio grows substantially and persistently should concerns be raised.
- The credit-to-GDP ratio alone may not be a sufficient indicator to distinguish risky episodes from welcome economic expansions resulting from improved fundamentals. But the combination of data on credit with information on asset prices, the cost of capital, bank capitalization, and realized ratios of credit to asset value may allow policymakers to better judge which force is prevailing.

In reality it is likely that all three shocks happen together, but after a few quarters the use of additional variables helps policymakers distinguish between the good and bad shocks. In other words, strong and persistent credit expansion that is accompanied by sharp asset price increases, a sustained worsening of the trade balance, and a marked deterioration in bank capitalization are suggestive of future problems for financial stability.

The Quest for Leading Indicators of Financial Sector Distress

The structural model in the previous section provides some helpful hints on the key indicators to signal rising systemic risk. Early recognition of the risk buildup phase is crucial to averting potential crises: it allows the financial sector time to accumulate capital and liquidity buffers and reduce risk taking. Many of these "leading" indicators are likely to come from relatively slow-moving, low-frequency, financial balance sheet aggregates.

Also required is the ability to predict with reasonable confidence the imminence of a period of high financial stress, so that policymakers are sufficiently prepared to manage an impending crisis, including by directing financial institutions to draw down their buffers to prevent financial disintermediation once the crisis sets in. Such short-range prediction must come from a second category of measures—"near-coincident" (high-frequency) indicators that, ideally, should provide enough lead time for policymakers to act. This set could also be used to trigger certain types of official sector responses, including, perhaps, some IMF lending

[15]This is not the loan-to-value (LTV) ratio imposed by banks, but literally the observed amount of credit for a given level of asset value.

[16]The ratio of credit to asset value actually declines slightly with the onset of an asset bubble because the bubble increases the value of assets that collateralize loans before lending increases enough to boost the ratio.

facilities. In short, two types of indicators are sought: leading, which signal well in advance that risks are building up; and near-coincident, which show that a crisis is about to materialize.

The empirical analysis in this section seeks to narrow down for policymakers a set of powerful and easily understood indicators for both the buildup and realization phases of systemic risk. By focusing on crisis episodes, the analysis ignores movements in credit associated with productivity gains—the type that is unlikely to lead to systemic stress. For the leading indicators, it uses information from the model described in the previous section to choose a set of variables that are associated with movements in credit aggregates. It is based on a broader sample (in terms of both countries and time periods) than previous studies, explicitly including the current crisis. And it uses a supplemental set of indicators (or "conditioning variables") that move together with credit aggregates: capital inflows, leverage indicators, asset prices, and real effective exchange rates.[17] For the near-coincident indicators, the analysis examines market-based indicators that have recently been proposed and ranks them using tests that distinguish their ability to signal stress in the financial system.

The analysis is guided by the following questions, which we address in turn below.

- What are the patterns followed by credit and other indicators in the lead-up to financial stress? Is there a specific credit measure that works best for this purpose?
- How can policymakers identify a buildup in risk without making costly mistakes? What are the thresholds beyond which the indicator signals financial crises at a reasonable forecasting horizon with a sufficiently high degree of certainty? (See also Box 3.2.)
- How much do credit aggregates and other indicators contribute to predicting a financial crisis?
- Among *near-coincident* indicators of financial stress, what is a robust set of high-frequency, market-based indicators that could be useful to put policymakers into alert mode? (See also Box 3.3.)

[17]Additional indicators are based on Shin (2010), Sun (2011), and IMF (2009). Ideally, also included would be the capital adequacy ratio, shown above to be informative; however, for the entire time period, it is available for only a few countries.

Event Study of Risk Buildup

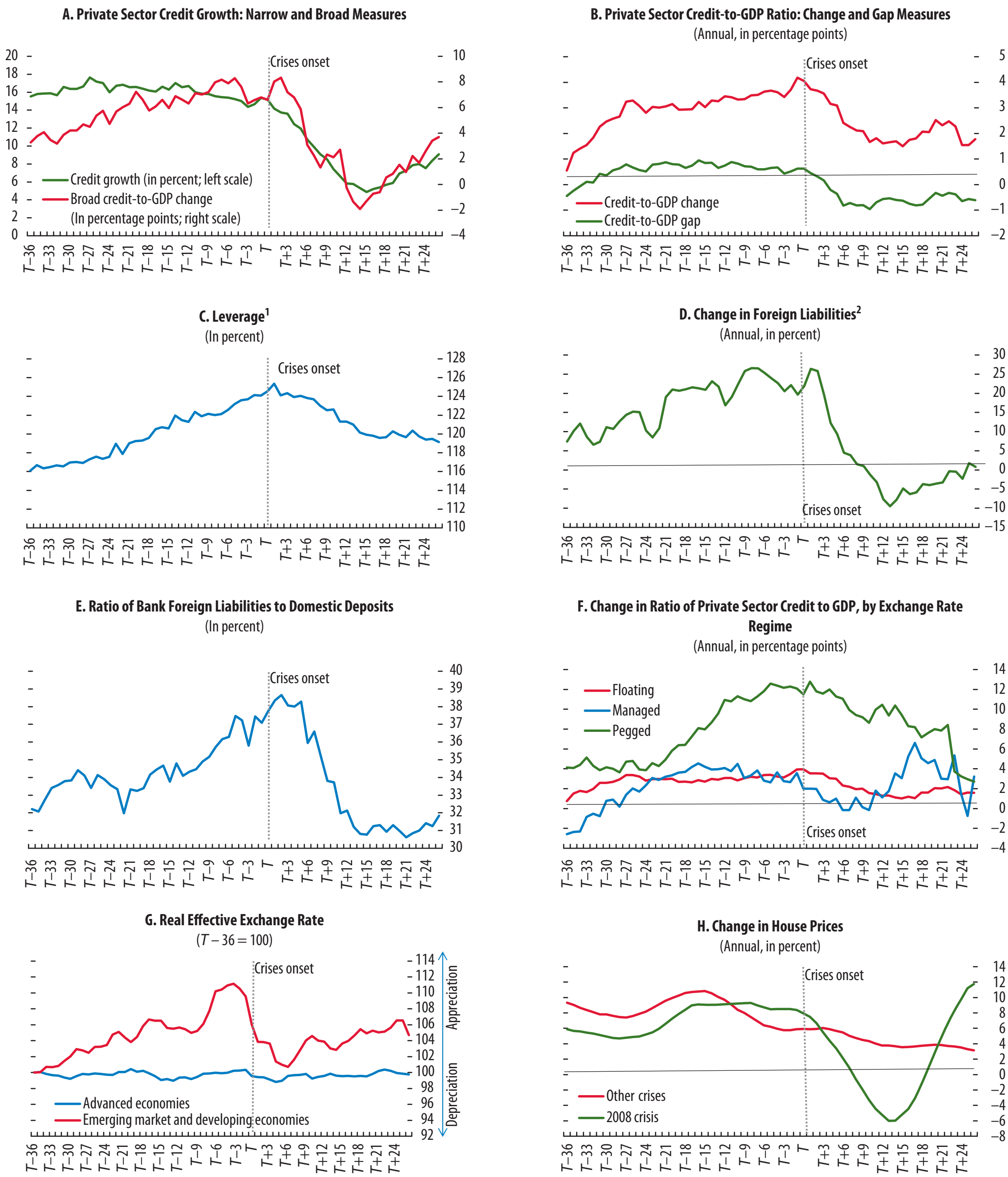
Various indicators move together with credit aggregates in the lead-up to severe financial stress episodes. An event study can help shed light on the levels and changes of these indicators one to three years before such episodes. The levels could give policymakers a broad sense of thresholds that can trigger concerns about risk buildup. The "event" in this case is severe financial stress identified—country by country—as extreme realizations of the Financial Stress Index (FSI) (IMF, 2008).[18] The month of the initial excess FSI realization is deemed to be the "signal" month for distress. Using this definition, 76 occurrences of financial distress across 40 countries have been identified in the monthly dataset. The main findings are as follows:

- Increases in the credit-to-GDP ratio above 3 percentage points, year-on-year, could serve as early warning signals one to two years before the financial crisis (Figure 3.3, panel B). Of all metrics of credit growth (Figure 3.3, panels A and B), changes in the credit-to-GDP ratio and changes in a broader measure of the credit-to-GDP ratio accelerate sharply before a crisis event occurs.[19] In

[18]The FSI is a monthly indicator of national financial system strain. See Cardarelli, Elekdag, and Lall (2011) for advanced economies; and Balakrishnan and others (2009) for emerging economies. This index—not to be confused with the Financial Soundness Indicators—relies on price movements relative to past levels or trends. For advanced economies, the index is the sum of seven variables, each of which is normalized to have a zero mean and a standard deviation of one: (i) the banking-sector beta (a measure of the correlation of bank equity returns with overall equity market returns); (ii) the TED spread (the difference between the three-month Treasury bill rate and the Eurodollar rate); (iii) term spreads (the difference between short- and long-term government bonds); (iv) stock market returns; (v) stock market volatility; (vi) sovereign debt spreads; and (vii) exchange market volatility. For emerging economies, the FSI comprises five variables (it excludes the TED and term spreads from the preceding list of seven and uses an index of exchange market pressure instead of exchange market volatility). See IMF (2008) for more details and Box 3.2 for details on the methodology. The average 5th percentile value of the FSI was 7.4 at the beginning of the 2007–09 financial crisis and 9.7 at its peak.

[19]The broader credit measure includes private-sector credit from banks (derived from monetary statistics) and cross-border loans to domestic nonbanks (derived from "other investment, liabilities" of international investment position statistics). The number of countries in the sample falls considerably when the broader measure is included.

Figure 3.3. Event Study Results: Aggregate Indicators Three Years before to Two Years after Crises



Sources: IMF, *International Financial Statistics*; OECD; Haver Analytics; Global Property Guide; and IMF staff estimates.
Note: *T* is month of crisis onset. For definition of broad credit, see text; for gap in credit-to-GDP ratio, see text and Box 3.2.
[1]Ratio of credit to deposits.
[2]Bank and private sector loans, deposits, and currencies.

Box 3.2. Extracting Information from Credit Aggregates to Forecast Financial Crisis

We examine three methods for analyzing credit aggregates to forecast a financial crisis: the event study, the noise-to-signal ratio, and the receiver operating characteristic.

Event Study

Severe financial stress is identified on a country-by-country basis at the 5th percentile upper tail of the Financial Stress Index (FSI) developed in IMF (2008).[1] Although tail occurrences tend to be clustered in successive months, identification is nontrivial, given that there may be temporary breaks in what, in principle, should be regarded as a single financial distress period. In this regard, we consider breaks of up to six months as being still within the same episode, with occurrences of financial distress immediately preceding and following a break forming one distinct episode. Once such distress episodes are fully identified, the month of the initial excess FSI realization is deemed to be the "signal" month for distress. In this fashion, 76 occurrences of financial distress across 40 countries are identified.

The analysis presented in Figure 3.3 uses windows of 36 months before and 24 months after a distress signal to examine the dynamics of a range of credit measures and financial balance sheet indicators, along with market-based indicators, for signs of a buildup of financial system instability. Credit measures are the annual change in nominal private sector credit, the annual change (in percentage points) in the private sector credit-to-GDP ratio, and the credit-to-GDP gap; the gap itself is measured as percentage point deviations from a recursive Hodrick-Prescott filter trend of the credit-to-GDP ratio, as in Drehmann, Borio, and Tsatsaronis (forthcoming). The analysis also considers measures of house prices, total and foreign-funded leverage (credit-to-deposit and foreign liability-to-deposit ratios), foreign liabilities, and exchange rate dynamics.

We use log-linear interpolation to create monthly frequencies for variables normally provided quarterly or annually—including GDP and capital flow measures.

Noise-to-Signal Ratio

A signaling exercise in the spirit of Drehmann, Borio, and Tsatsaronis (forthcoming) is conducted using noise-to-signal ratios (NSR) for a set of 169 countries (depending on the specification) that includes advanced, emerging, and low-income economies.[2] The NSR for different prediction horizons (lags) provides a summary picture of what thresholds routinely predict crises for different indicators and for different countries. Using annual data and the Laeven-Valencia crisis measure (LV) as an indicator for financial stress/crisis (Laeven and Valencia, 2010), the predictive capacities of three variables—change in the credit-to-GDP ratio, change in a broad measure of the credit-to-GDP ratio (which includes cross-border loans to the private sector), and the gap in the credit-to-GDP ratio—are analyzed at horizons ranging from one to five years before the crisis event. All results have been determined in-sample, drawing upon previous research indicating that the selected indicators also perform well out-of-sample (Borio and Drehmann, 2009).

The signaling methodology works as follows:

- For each signaling variable—changes in alternative measures of credit-to-GDP and the credit-to-GDP gap—a certain threshold is defined, based on the historical performance of

Noise-to-Signal Ratios: An Example

	Crisis occurs within a 3-year window starting *k* years after the signal	Crisis does not occur within a 3-year window starting *k* years after the signal
Indicator signaling *k* years ahead	A	B
Indicator not signaling *k* years ahead	C	D

Note: The indicator is lagged *k* years, for $k = \{1,2,3,4,5\}$.

Note: Prepared by Silvia Iorgova, Christian Schmieder, and Tiago Severo.

[1]The FSI is a monthly indicator of financial system strain. The index relies on price movements relative to past levels or trends. See the main text for details.

[2]The exact number of countries depends on the details of each exercise, since the availability of information varies as different crisis measures and macroeconomic variables are included in the computations.

Box 3.2 *(continued)*

the measure. Various thresholds are considered: annual increases above 3 percent, 4 percent, or 5 percent for changes in credit-to-GDP or observations above 1, 1.5, or 2 standard deviations beyond the sample mean for the gap.[3] A dummy variable is created, assuming the value of 1 if the signaling variable is above the threshold and zero otherwise. This dummy is the “crisis signal.” The predictive value of the “crisis signal” is then assessed according to whether it predicts a crisis—determined by the LV variable—in at least one period in a window of three years. The crisis signal is lagged k years, where $k = \{1,2,3,4,5\}$. More specifically, the test is whether a value of 1 for a certain “crisis signal” at time t is followed by a value of 1 for the LV measure on at least one of the dates $t + k$, $t + k + 1$, and $t + k + 2$. If that is the case, the signal is correct. A failure to signal a crisis that actually happens produces a Type I error—C/(A + C) in the diagram above—whereas a false signal (a signal that is not followed by a crisis in the future) produces a Type II error—B/(B + D) in the diagram.

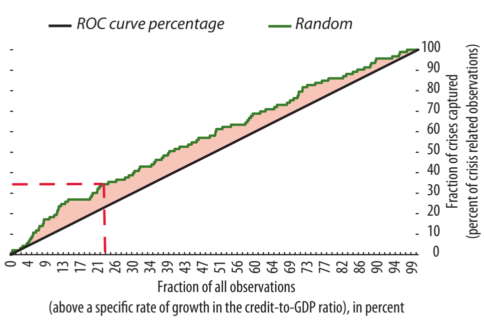
- The two types of errors are compared by means of the NSR, which is defined as the proportion of Type II errors divided by 1 minus the proportion of Type I errors. A “crisis signal” with a small NSR is able to forecast a large number of crises without sending an excessive number of false signals. A higher NSR, on the other hand, results from a combination of missing actual crises and producing too many false signals.

Receiver Operating Characteristic (ROC)

The receiver operating characteristic (ROC) is a graphical method for determining the discriminatory power of signaling variables. This analysis, which uses the same dataset as the NSR, first plots the share of (crisis- and noncrisis-related) observations based on a pre-specified order of the signaling variable along the x-axis. For example, suppose a change in the credit-to-GDP ratio of 3 percentage points or greater is 23 percent of all observations. Then the 23 percent value for the signaling variable on the x-axis would be associated with these levels of credit growth. To obtain a larger share of the observations moving to the right on the x-axis, lower thresholds are required. To obtain the corresponding y-axis value, one compares credit-to-GDP growth of 3 percentage points or greater with the number of crises in the sample. The proportion of crises at this level (34 percent) is plotted on the y-axis. In that sense, each point on the ROC curve corresponds to the percentage of predicted crises (and the corresponding number of all observations, which determines false signals) given a specific threshold, in this case, the greater than 3 percentage point change in the credit-to-GDP ratio.

The predictive power of the signaling variable (in this case credit-to-GDP change for emerging economies) is determined by the area between the ROC curve and the 45-degree line (the shaded area in the figure below). The 45-degree line in the figure corresponds to an area of 0.5 and is equal to random sampling of both the x- and y-axis variables, which means that a ROC curve lying on the 45-degree line does not indicate any predictive power. In the example shown below, the area is 0.57 (the area under the ROC for emerging economies in Table 3.2); that is, the shaded area is 0.07. As shown by the dashed lines

Example of an ROC Curve for Growth in the Ratio of Credit to GDP
(In percent)



Source: IMF staff estimates.
Note: Area under the receiver operating characteristic (ROC) curve is 0.57, which corresponds to the entry for emerging economies in Table 3.2. For data indicated by shaded area and dashed lines, see box text.

[3]Importantly, both the average gap and the standard deviation are country specific, to take into account the large variation in these measures across the countries considered.

Box 3.2 *(continued)*

in the figure, a threshold of 3 percentage points for growth of the credit-to-GDP ratio (which corresponds to an x-axis value of 23 percent), for example, captures about 34 percent of all crises (resulting in a Type I error of 0.66).

Depending on how many crises one seeks to identify on the one hand and how many false signals one tolerates on the other, one can calibrate a threshold accordingly. Generally, clustering of crisis observations within low percentiles (depending on the specific underlying order of the signaling variable) indicates higher discriminatory power for the signaling variable. Hence, while the total area under the curve provides a proxy for the predictive power in general, high levels of predictive power will be associated with the signaling variable performing well for the lowest percentiles of observations on the x-axis. Using a multivariate measure improves the predictive power, for example by using the outcome of the probit regression documented in Annex 3.2.

fact, the broader credit growth measure accelerates even more: its change averages 5 percentage points of GDP two years before the crisis and goes up to 7 percentage points of GDP one year before the crisis. In the aftermath of distress, this measure also drops the most.

- The nominal year-on-year rate of credit growth does not seem to accelerate ahead of a crisis (Figure 3.3, panel A). However, the "gap" measure of the credit-to-GDP ratio tends to be persistently positive before distress episodes (Figure 3.3, panel B).[20]
- Credit-to-deposit ratios higher than 120 percent are associated with crises within the next year (Figure 3.3, panel C).
- Foreign liabilities of the private sector typically accelerate rapidly before a crisis. External borrowing by banks and the nonbank private sector grows from around 10 percent to 25 percent in the run-up to financial stress (Figure 3.3, panel D). Following a stressful episode, these liabilities fall dramatically for the next 12 months.[21]
- Banks' foreign liabilities as a fraction of domestic deposits increase from about 32 percent to 38 percent two years before a crisis (Figure 3.3, panel E).[22]
- Countries with fixed exchange rates have much higher credit growth than average (Figure 3.3, panel F). This reinforces the findings from the structural model that any shock propagates more strongly in a fixed or managed exchange rate regime.
- Real effective exchange rates (REER) tend to appreciate rapidly in the run-up to the crisis in emerging economies (Figure 3.3, panel G). For example, the rapid credit expansion preceding the 2008 global crisis was associated with an increase in the REER (an appreciation) of around 4 percent for most of the precrisis years. As discussed in the previous section, the persistent deterioration in the trade balance resulting from an asset price bubble shock could be related to the rise in

[20]The credit-to-GDP gap (Borio and Drehmann, 2009; and Drehmann, Borio, and Tsatsaronis, forthcoming) and change in the credit-to-GDP ratio are prime candidates for comparison. The former is the deviation of the credit-to-GDP ratio from a recursive Hodrick-Prescott filter trend. The advantage of the gap measure is that it is cumulative and takes into account the country-specific trend. Its disadvantage is that a gap of zero could still reflect a very high rate of credit growth, which is the core concern for financial stability. In the same vein, the indicator is less convenient for policy purposes, and ultimately macroprudential policies will have to target credit growth as such (that is, the gap has to be translated back into credit growth). The advantage of the ratio measure is that it readily focuses on the pace of credit growth. Its main disadvantage is that it omits cumulative aspects.

[21]In this context, foreign liabilities refer only to loans and deposit liabilities of the private sector and are taken from balance of payments statistics (changes in the international investment position for banks and nonbanks under "other investment, liabilities"). Instead of focusing on the current account deficit, only the above set of capital inflows are emphasized here, since countries reliant on such flows have been more prone to the recent crisis, at least in emerging Europe (Cihak and Mitra, 2009).

[22]This measure could be interpreted as a measure of noncore/core liabilities, which tend to grow with assets. See Shin and Shin (2011).

the real exchange rate (Figure 3.2). The relentless increases in the price of nontradables that included housing services resulted in real appreciation of the currency before the recent crisis in some regions of the world.

- House prices, on average, tend to rise by 10 to 12 percent for two years before financial sector stress emerges.[23] This pattern is in line with previous studies showing that house prices are a strong leading indicator of potential financial distress (Kannan, Rabanal, and Scott, 2009b) or associated with rapid credit growth (Claessens, Kose, and Terrones, 2011a and 2011b) (Figure 3.3, panel H).

Echoing the implications of the structural model in the previous section, these results suggest that even though credit growth is potentially a good leading indicator, it may not be sufficient to determine the timing and extent of a risk buildup. Rather, other variables should be considered alongside it. The results above suggest that if asset prices are increasing, the real exchange rate is appreciating, bank and corporate cross-border funding are going up, and leverage is increasing, then there is a reasonable chance of facing an episode of financial stress within the next couple of years. The following subsections reinforce this point and derive meaningful thresholds of the leading indicators that would allow policymakers to issue signals of future financial stress.

Exploring the Costs and Benefits of Issuing Signals Based on Leading Indicators

Using early warning indicators to identify the buildup of financial risk entails two potential problems. There could be cases in which policymakers fail to predict a financial crisis that later occurs (called a Type I error) because thresholds were set too high. Alternatively, there could be instances in which early warning indicators exceed their thresholds but financial system stress does not materialize (called a Type II error). Ideally, the signaling power of indicators should minimize both types of errors. Naturally, there is a trade-off. For instance, minimizing Type I errors encourages setting thresholds low, creating frequent false signals (Type II error).

To observe the ability of different slow-moving variables to properly balance Type I and Type II errors, two statistical methods are used:

- Noise-to-signal ratio (NSR): The NSR is the ratio of false alarms to legitimate alarms, that is, a summary of Type I and Type II errors.[24] The lower the NSR, the better is the signaling power of a particular indicator (Box 3.2).
- Receiver operating characteristic (ROC): The ROC is a graphical tool that weighs the benefit of decreasing the thresholds of indicators (to lower the chance of missing a crisis) versus the cost of issuing a false signal (Box 3.2). It provides a summary measure of the signaling ability of an indicator. The more the measure exceeds 0.5, the better is the indicator's signaling ability.

Noise-to-Signal Ratio

The NSR is computed from annual data for 169 countries, with 109 crisis episodes identified by Laeven and Valencia (2010).[25] A three-year window is set, as it is in the event study, and the indicator variable was lagged two periods (Table 3.1). For example, if the credit-to-GDP ratio exceeds the threshold at year t and a crisis occurs at years $t + 2$, $t + 3$, or $t + 4$, then the signal is successful.[26] The findings suggest that:

[23]Equity prices are a part of the FSI indicator and hence tend to be contemporaneous with distress window peaks. For this reason, equity prices were not included in the event study.

[24]The noise-to-signal ratio is defined as the proportion of Type II errors (cases with indicator signaling a crisis as a fraction of cases in which crisis did not occur) divided by the proportion of legitimate signals (cases with indicator signaling a crisis as a fraction of cases in which crisis did occur). See Kaminsky, Lizondo, and Reinhart (1998); Berg and others (2000); and Box 3.2.

[25]The Laeven-Valencia index of episodes is a broad, coincident indicator for full-blown financial crises that uses government intervention in the financial sector to date the episodes. On the other hand, the FSI used in the previous section is an indicator of financial stress that might not materialize into a full-blown crisis. The advantage of the LV index is that it covers 169 countries rather than the 40 countries covered by the FSI, but a considerable drawback is its annual frequency and the scarcity of crisis occurrences—at most one crisis per country for most countries and 109 overall.

[26]The sample is reduced for different indicators based on data availability. Results are similar for a one-year lag.

Table 3.1. Noise-to-Signal Ratios for Different Credit Indicators
(In percent unless noted otherwise)

Crisis Measure	Warning Signal Issued When	Thresholds	Average NSR for Countries (at least one forecasted crisis)	Number of Countries	Average Type I Error	Average Type II Error	Fraction of Countries with 100% Type I Error
Laeven and Valencia (2010)	Credit-to-GDP gap is:	1 std > mean	0.07	82	65	8	61
		1.5 std > mean	0.05		84	3	80
		2 std > mean	0.04		95	1	94
	Percentage change in credit-to-GDP is larger than:	3	0.38	78	17	37	15
		5	0.33		22	31	21
		7	0.29		36	25	33
	Percentage change in broad measure of credit-to-GDP is larger than:	3	0.18	8	0	18	0
		5	0.11		0	11	0
		7	0.18		13	6	0

Source: IMF staff estimates.

Note: The numbers were computed for 2 lags of the signaling variable. The table reports the average NSR for all countries in a given group. Low values for the NSR indicate that a certain credit measure is able to accurately predict a large number of crises for many countries.

- The credit-to-GDP gap does not perform well as a signaling variable. It misses too many crises. Conditioning on extra variables only makes things worse. It is worth noting that if the sample is restricted to advanced countries, the performance improves.[27]
- The change in the credit-to-GDP ratio is more promising, as it misses only a moderate number of crises. Nonetheless, it induces frequent Type II errors. For instance, the average Type II error associated with the change in credit-to-GDP ratio is much higher (25 percent or higher) than for the credit-to-GDP gap (at most 8 percent). This problem may be mitigated with the inclusion of additional conditioning variables, such as asset price growth.
- The analysis based on the change in the broad measure of the credit-to-GDP ratio can be applied to only eight countries. The broad measure includes not only bank credit but also direct cross-border credit to the nonbank private sector.[28] The results improve substantially in this case. A 5 percentage point threshold captures all of the crises; that is, the average Type I error is zero (Table 3.1).

The findings from the NSR exercise and the event study suggest that the yearly change in the credit-to-GDP measure is best among credit aggregates in signaling a crisis. However, the analyses also indicate that a credit aggregate alone may not be a sufficiently good leading indicator, especially when considering a large sample of countries. As illustrated by the structural model, increases in credit aggregates may reflect benign responses of the economy to positive shocks to fundamentals, with muted effects on systemic risk. This implies that other conditioning variables that co-move with credit aggregates could complement the analysis, especially if these additional indicators allow policymakers to reduce Type II errors without increasing Type I errors too much.

Receiver Operating Characteristic (ROC)

The receiver operating characteristic (ROC) uses the annual data with Laeven-Valencia crisis dates to determine the predictive power of various slow-moving indicators (Box 3.2). The ROC summarizes the costs and benefits of choosing various thresholds of an indicator ranging from high to low—a richer set of possible choices. The higher its ROC above 0.5, the better is a variable's predictive power (Table 3.2).[29] Both the credit-to-GDP gap and the growth in the credit-to-GDP ratio are included in the analysis, along with asset prices, real exchange rate changes, and growth in banks' foreign liabilities. The analysis confirms that establishing clear thresholds for credit variables to identify crises is difficult and depends heavily on policymakers' preferences for implementation methods.

- If a policymaker's preference is to target "clear" cases, that is, to limit false signals, then thresholds should be set very high. Setting a threshold for the change in the credit-to-GDP ratio at the upper 20th–30th percentile in historical terms, for example, will help signal between 30 percent and 40 percent of the crises in both emerging markets and advanced countries.
- On the other hand, if the objective is to identify a larger number of crises, say 60 percent of them, then one has to accept a substantially higher number of false signals, as the threshold for credit-to-GDP change has to be set at the upper 45th–50th percentile in historical terms.
- A key finding for macroprudential policy is that asset price growth signals crises earlier than measures of credit growth, for both advanced and emerging economies. Credit growth peaks one to two years before crises, whereas both equity and house price growth are at their highest two to five years ahead of crises.
- The predictive power of other conditioning variables (exchange rates, foreign liabilities) peaks at about a year in advance. Table 3.2 confirms the

[27]Borio and Drehmann (2009), who advocate this measure, consider a small set of advanced economies only.

[28]The stock of cross-border loans is derived from other investment liabilities data from the balance of payments of the IMF's *International Financial Statistics* (IFS). The latter source of data was chosen to maintain consistency with data on credit, which comes from the monetary statistics of the IFS. However, the number of countries fall dramatically both because of data availability and coverage of the Laeven-Valencia index.

[29]If the predictive power of an indicator is very low, then it is hard to choose meaningful thresholds for it.

Table 3.2. Predictive Power of Various Indicators "X" Years before the Crisis

		Only Crisis Observations X Years before Crises					All Crisis Observations		
	All Crisis Observations	1 year	2 years	3 years	4 years	5 years	Advanced countries	Emerging markets	Low-income countries
Credit-to-GDP gap	0.54	0.60	0.56	0.57	0.49	0.49	0.59	0.53	0.53
Equity price gap	0.59	0.54	0.55	0.56	0.68	0.61	0.56	0.58	0.61
House price gap	0.58	0.55	0.59	0.54	0.60	0.63	0.65	0.51	0.62
Credit-to-GDP (year-on-year change)	0.54	0.61	0.55	0.54	0.54	0.49	0.62	0.57	0.48
Equity price (year-on-year change)	0.67	0.67	0.67	0.66	0.71	0.62	0.71	0.69	0.63
House price (year-on-year change)	0.57	0.52	0.59	0.58	0.55	0.60	0.65	0.57	0.52
Real effective exchange rate	0.56	0.61	0.58	0.53	0.53	0.56	0.59	0.52	0.59
Foreign liabilities (year-on-year change)	0.50	0.67	0.50	0.58	0.28	0.34	0.63	0.44	0.68

Source: IMF staff estimates.

Note: The crisis indicator is the Laeven-Valencia index. The table shows the area under the ROC curve (see Box 3.2). An area under the ROC curve of 0.5 indicates that there is no additional discriminatory power compared with random sampling. The higher the number (which is bounded at 1) above 0.5, the higher is the discriminatory power. Number of observations is low in some cases.

earlier result that the change in the real effective exchange rate can be a good conditioning variable.

- Indicators related to equity prices have the highest predictive power, followed by those related to house prices (Table 3.2). The structural model also identified these asset price indicators as having the potential to identify the type of shock hitting the economy, and could indicate excessive optimism by investors.

Panel Data Regressions

A more formal estimation of the relationship between slow-moving variables and the probability of financial crises confirms that both credit measures—the credit-to-GDP gap and the change in the credit-to-GDP ratio—have a statistically significant effect on crisis probabilities. As is common in many of these types of studies, however, the estimated probability of a systemic banking crisis is small (see Annex 3.2).[30]

- Generally, the relationship is strongest at a forecast horizon of one to two years. This confirms the observations based on the event study, the NSR, and the ROC.
- For a high-risk country, a 1 percentage point increase in the credit-to-GDP gap or an annual 1 percentage point increase in the credit-to-GDP growth will increase the probability of a systemic banking crisis by 0.2–0.3 percentage point in each of the following two years.[31]
- However, the probability of a crisis accelerates as credit growth (both the gap and change measures) increases from the median to the 90th percentile (in sample).
- When other indicator variables are interacted with credit aggregates, the probability of a systemic crisis increases.[32] This is evident with equity prices, confirming results from the NSR and ROC analyses. If growth of the credit-to-GDP ratio is at 5 percentage points, then an equity price increase of 10 percent increases the probability of a systemic financial crisis to more than 15 percent within the next two years (Figure 3.4).
- The model is able to forecast crises out-of-sample as well. Using just one country as an example, if the panel model is estimated up to 2000, credit aggregates help forecast the recent crisis in the United States well (Figure 3.5 and Annex 3.2).

Near-Coincident Indicators of Imminent Crisis

High-frequency indicators are best at informing policymakers of imminent severe financial stress. The credit aggregates and other low-frequency indicators cannot inform policymakers of imminent financial distress or the onset of a crisis. For instance, some balance sheet aggregates continue to increase well after a systemic stress is detected (see Figure 3.3). To signal imminent stress and crisis, near-coincident indicators are required. A version of conditional Value at Risk, or CoVaR (Adrian and Brunnermeier, 2010), that varies with the LIBOR-OIS spread and the yield curve, is a high-frequency, market-based measure that appears to be a good near-coincident indicator (Box 3.3).[33] Other high-frequency market-based indicators do well on other counts but not necessarily on average for all counts.

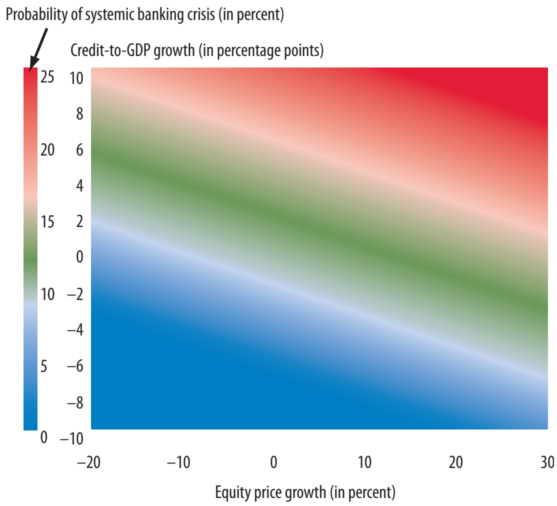
[30]A probit (unbalanced panel data) model with country fixed effects is estimated across 94 countries (with advanced, emerging, and low-income economies) over 1975–2010 using annual data. The fixed effects of a country denote the time-invariant characteristics that affect the crisis probability; a country with very high fixed effects (80th percentile) is termed "high risk." Using the Laeven and Valencia (2010) definition of crisis in the form of a crisis dummy (1 for crisis and 0 otherwise), the estimation evaluates the ability of the different indicators to explain the probability of crises at three different forecast horizons—one, two, and three years.

[31]See Annex 3.2 and Table 3.4 for medians based on data for 94 countries and methodological details.

[32]The estimation of the multivariate probit model is based on a smaller dataset because of data gaps for equity prices. The dataset shrunk further when other variables were included. Even so, indicators like the growth in foreign liabilities and the level of the loan-to-deposit ratio were tested and found to increase the marginal effect of credit aggregates on the probability of crisis.

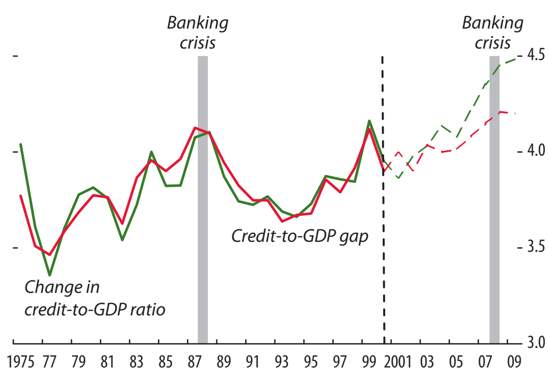
[33]The CoVaR is the Value at Risk of the financial system conditional on institutions being under distress. An institution's contribution to systemic risk is the difference between the CoVaR for tail-risk episodes and the CoVaR at the median state. The time-varying CoVaR is estimated by quantile regressions of the returns of the financial system on the returns of an institution and other state variables. The latter includes the yield curve (the difference between interest rates on long-term Treasury bonds and short-term Treasury bills) and the spread between the London Interbank Offered Rate (LIBOR) and the overnight indexed swap (OIS).

Figure 3.4. Probability of a Systemic Banking Crisis



Source: IMF staff estimates.
Note: The figure is based on a panel probit model with country fixed effects. See Annex 3.2 for estimation results. The data are from an unbalanced annual panel that lies within the period 1975–2010. The estimation with equity price growth is at a two-year forecast horizon and is based on 36 countries with 27 crises observations. The probabilities are evaluated at the 80th percentile fixed effect (high-risk country). The crisis probability ranges from 0 (blue) to 25 percent (red).

Figure 3.5. Estimated Probability of a Systemic Banking Crisis in the United States: Effect of Changes in Credit
(In percent)



Source: IMF staff estimates.
Note: The forecast of crisis probability for a given year is made in the preceding year. Probabilities are based on two panel probit models with fixed effects for 1975–2000, one with the change in the credit-to-GDP ratio and one with the credit-to-GDP gap; see text and Box 3.2. The dashed lines show the out-of-sample probabilities for 2001–09. See Annex 3.2 for details on calculation of probability.

However, the market-based indicators do not necessarily signal rising interconnectedness of the financial system well ahead of time. If policymakers could read market signals of interconnectedness—an institutions' rising contribution to systemic risk—early enough, then they could make these institutions pay (for example through capital or liquidity surcharges) for their risk taking.[34] The inability of the market to pick up interconnectedness could be due to the nontransparency of inter-institution exposures that do not enable market discipline early on.

The findings from this section can be summarized as follows:

- Among the credit aggregates, a threshold of 5 percentage points for annual change in the credit-to-GDP ratio works reasonably well in signaling crises: it reduces the chances of missing a crisis without a correspondingly high number of false signals. Thresholds for the credit-to-GDP gap are harder to determine, and those analyzed for advanced and emerging economies tend to miss most crisis episodes. Thresholds for a broader credit measure—that combines data on bank credit and cross-border credit—work well, but the analysis is hindered by data gaps.
- The panel regressions show that both credit growth measures are almost equally good in predicting crises at one- to two-year horizons, even though the predictive power for either measure is moderate. The gap performs better at a one-year horizon, whereas the growth rate is a better signal two years ahead.
- Other indicator variables need to be taken into account while applying thresholds for credit aggregates. Real exchange rate appreciation (especially for emerging economies) and growth in equity prices are prime candidates.
- Among high-frequency near-coincident indicators, the best performer is the time-varying CoVaR. Given that this indicator builds on the yield curve and LIBOR-OIS spread, among other data, some combination of the yield curve and LIBOR-OIS

[34]IMF (2010a) provides a method of calculating a systemic solvency surcharge based on interconnectedness; IMF (2011a) provides such a surcharge for systemic liquidity risk.

Box 3.3. Risk Materialization: The Search for Near-Coincident Indicators of Financial System Stress

High-frequency market-based indicators best inform policymakers that a systemic event or crisis is imminent ("near-coincident" indicators). Such signals can then be used by policymakers to request that accumulated capital or liquidity buffers be released; or the indicators can be built into macroprudential measures to effect the release automatically. Various econometric techniques are used to determine robustness in a group of near-coincident indicators of systemic financial stress. The findings suggest that an indicator combining information from the yield curve and the LIBOR-OIS spread works best for the United States. However, the tested indicators did not perform well in flagging the rising interconnectedness of Bear Stearns and Lehman Brothers before their respective failure.

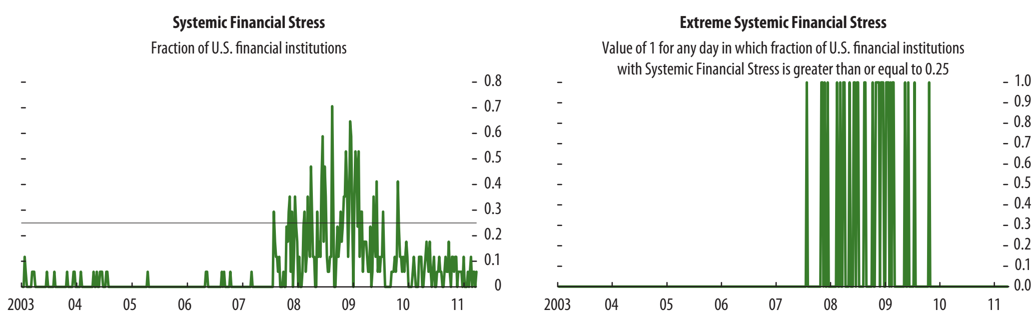
The current crisis is used as a testing ground for various high-frequency indicators, and two new indicators for ongoing stress specific to the financial sector are introduced (see Annex 3.3 for definition of the indicators and calculations). The first is "systemic financial stress," or SFS (first figure, left panel). An SFS of, say, 0.10 means that 10 percent of financial institutions in the system experienced large negative abnormal returns on a given day as well as negative abnormal returns for the two weeks following that day.[1] A second measure, a subset of SFS observations, is "extreme SFS," defined as an SFS equal to or larger than 0.25 (first figure, right panel). For the United States, the SFS helps predict changes in the real economy.[2] The set of high-frequency near-coincident indicators is then tested against both the SFS and its extreme form.

Note: Prepared by Srobona Mitra, drawing on Arsov and others (forthcoming).

[1]The SFS is calculated using equity returns of 17 domestic financial institutions from the United States for weekly data for the period 12/30/2002–4/11/2011. Abnormal returns are defined by banks' weekly equity returns *minus* overall market stock returns. For the United States, for instance, the return on the S&P 500 index is taken as the market return. The threshold for large negative abnormal returns is based on the 5 percent left tail of the joint distribution of abnormal returns for 17 domestic financial institutions for the United States. The Financial Stress Index (FSI) from IMF (2008), which is monthly, and the monthly version of the SFS seem to forecast (Granger-cause) each other. The SFS is a high-frequency measure of stress specific to a group of financial institutions, whereas the FSI is a broader measure of financial stress.

[2]The monthly version of the SFS for the United States helps forecast current-year's GDP growth (as shown by Granger Causality tests of the SFS and GDP growth forecasts from Consensus Economics) but not necessarily next years' GDP growth.

Systemic Financial Stress in the United States



Sources: Bloomberg; Datastream; and IMF staff estimates.

Box 3.3 *(continued)*

The performance of the 10 indicators in signaling the materialization of risk is judged by their scores on each of three tests:[3]

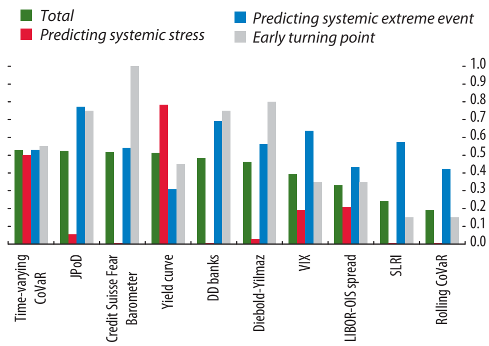
- Predicting SFS at a reasonable horizon.[4]
- Predicting extreme SFS with reasonable likelihood.[5]
- Providing an early turning point (early breakpoints in the level and persistence process of the variable).[6]

The 10 near-coincident indicators of systemic risk are then ranked by the average scores—from 0 (worst) to 1 (best)—on the three tests (see Annex 3.3 for details).

Based on the scores, the time-varying conditional Value at Risk or CoVaR—which takes into account two additional time-varying variables in the methodology: (i) a yield curve (the spread between the 10-year Treasury bond and the 3-month Treasury bill) and (ii) the LIBOR-OIS spread—is the best overall performing "near-coincident" indicator (second figure). The joint probability of distress (JPoD) is able to forecast extreme systemic stress events (or tail-risk scenarios) well but, like the distance to default (DD), does less well in forecasting stress in general. The yield curve by itself is best at signaling systemic stress events (the SFS), and the Credit Suisse Fear Barometer has the earliest turning point.

There are some indicators (out of the 10 studied here) that also have some component that measures interconnectedness in the financial system by calculating the contribution of an institution to systemic risk—the CoVaR, the Diebold-Yilmaz spillover index, and the JPoD are examples.[7] How

Performance of Near-Coincident Indicators in Predicting Severe Stress Early Enough, by Indicator and Three Metrics
(Index: 0–1, higher the better)



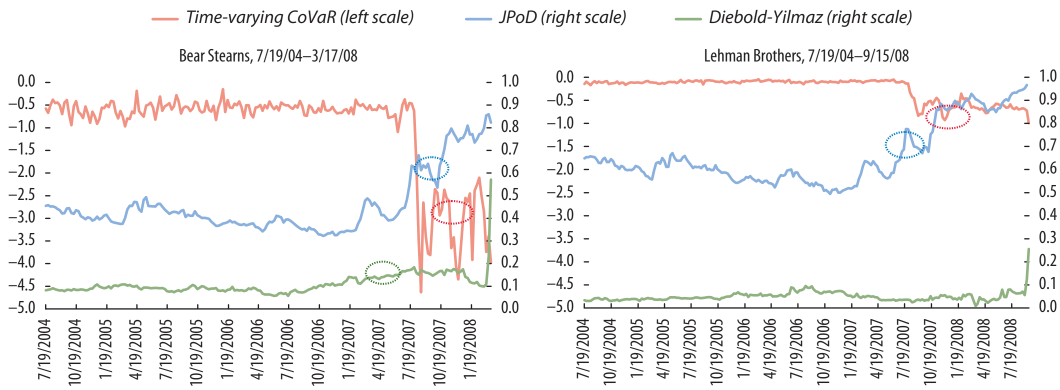
Sources: Bloomberg; Datastream; and IMF staff estimates.
Note: See Annex 3.3 for an explanation of the indicators and for details on how the three metrics were estimated.

well do these indicators signal a rise in interconnectedness of the system? Two institutions' contributions to systemic risk are tracked using the three indicators until the date the institutions were deemed to have failed.[8] As shown by the third figure, the time-varying CoVaR does not necessarily indicate rising interconnectedness before the other indicators. On the other hand, the Diebold-Yilmaz had indicated, as early as end-2006, that the contribution of Bear Stearns to systemic risk spillovers was 15 percent—larger than what could be inferred from its relative asset size among the group of financial institutions analyzed here. However, Diebold-Yilmaz does not signal the potentially high contribution of Lehman Brothers. The other two indicators do signal rising interconnections of the two failed institutions, but not far enough in advance for policymakers to take action before crisis has set in.[9]

[3]See Rodríguez-Moreno and Peña (2011) for a related exercise, the conclusion of which is the "simpler the better."
[4]Given by Granger Causality tests at various horizons. Scores based on *p*-values.
[5]Logit tests are performed with extreme SFS as the dependent variable (0–1) and the lagged dependent and lagged indicator variable as explanatory variables. Scores are based on *p*-values of Wald tests and McFadden *R*-squares.
[6]Quandt-Andrews breakpoint test for unknown breakpoints for the level and persistence parameters of an AR(4) model of each indicator. Score based on the earliest breakpoint.
[7]See Schwaab, Koopman, and Lucas (2011) for a discussion of different purposes of high-frequency indicators.
[8]Bear Stearns was sold to JPMorgan Chase, and Lehman Brothers was placed into bankruptcy.
[9]The JPoD, for instance, shows a trend decline in interconnections before 2007 for the two failed institutions.

Box 3.3 *(continued)*

Interconnectedness: Contribution to Systemic Risk of Two Failed Institutions



Source: IMF staff estimates.

Note: See text for explanations of the indicators. The time-varying conditional Value at Risk (CoVaR) for each of the institutions denotes the VaR of the financial system conditional on the VaR of each of the institutions falling from its median to the lowest 5th percentile of returns (in percent). The joint probability of default (JPoD) for each institution denotes the probability (in percent) that at least one other institution defaults when the subject institution defaults. The Diebold-Yilmaz for each institution denotes the contribution of each institution's spillover risks to all other institutions as a fraction of all outward spillovers of all institutions. The circles denote the turning points in the levels of the indicators.

spread could be used effectively in a large set of countries.

- No market-based indicator tested here serves to alert policymakers to rising interconnectedness in the financial system, probably because the transparency and disclosure of information on interconnectedness is currently insufficient.

Macroprudential Indicators and Policies: Stitching Them Together

After identifying the buildup of systemic risk, authorities need policies well suited to deal with the problem. Ideally, the policies would reduce financial risk taking—so as to limit the buildup in the identified financial imbalances—and accumulate buffers to be drawn down during crisis. As the policy would aim at reducing the procyclicality of banks' risk taking, that is, reduce the financial sector's exposure to systemic risk, it would be implemented over and above microprudential requirements.[35]

Many countries, especially emerging economies, have experimented with various policy tools to manage systemic risk.[36] Some policies have indeed been effective in lowering the sensitivity of real GDP growth to financial aggregates, like credit growth and leverage. For instance, lending caps based on loan-to-value (LTV) ratios and the debt service-to-income ratio and direct limits on credit growth have worked to reduce procyclicality. Dynamic provisioning—setting aside loan-loss provisions at the beginning of the risk-taking cycle to be drawn when the cycle takes a downturn—has worked to reduce the procyclicality of both credit and leverage. In contrast, instruments like countercyclical capital requirements to build buffers are untested. Yet, capitalization was identified as an indicator that would persistently decline in response to the perverse shocks discussed previously and could be used as a buffer.

The structural model introduced above is invoked below, in two cases, to illustrate the effectiveness of

[35]See IMF (2011b).

[36]Box 3.4; Lim and others (forthcoming); Terrier and others (2011).

macroprudential policies using countercyclical capital buffers as an example. As will become clear in the discussion, proper application of macroprudential instruments could prevent crises and reduce the volatility of financial and real variables in the long run, a desirable outcome. The buffer-building stage could be informed by credit aggregates, possibly the broad credit-to-GDP ratio, and other indicators like asset price growth, leverage, and real exchange rate changes, as noted above. The drawdown stage could be informed by sudden changes in indicators that combine information on the yield curve and the LIBOR-OIS spread, for instance. However, the benefits have to be compared with the potential costs. For instance, macroprudential regulation could lower output and consumption growth and reduce financial intermediation in the medium term, considerably so if policymakers do not understand the source of the financial and real imbalances in the economy.

The objective of the macroprudential policy sought here is to reduce a severe disruption in financial services and output losses by containing the cycles in financial risk.[37] Instead of the traditional welfare analysis, in which welfare improves with consumer utility, the analysis here seeks to minimize the *cumulative* sum of squared deviations from the baseline in output, inflation, consumption, and credit following a crisis. As an illustration, the model assumes that the underlying movements in key variables are generated by an asset-price bubble, but it can also be used to combine two or more shocks to mimic real-world events.

Could this same macroprudential tool—countercyclical capital buffers—be effective for different types of economies? As an illustration, the exercise now considers two different economies: one with a fully flexible exchange rate and another with a managed exchange rate.

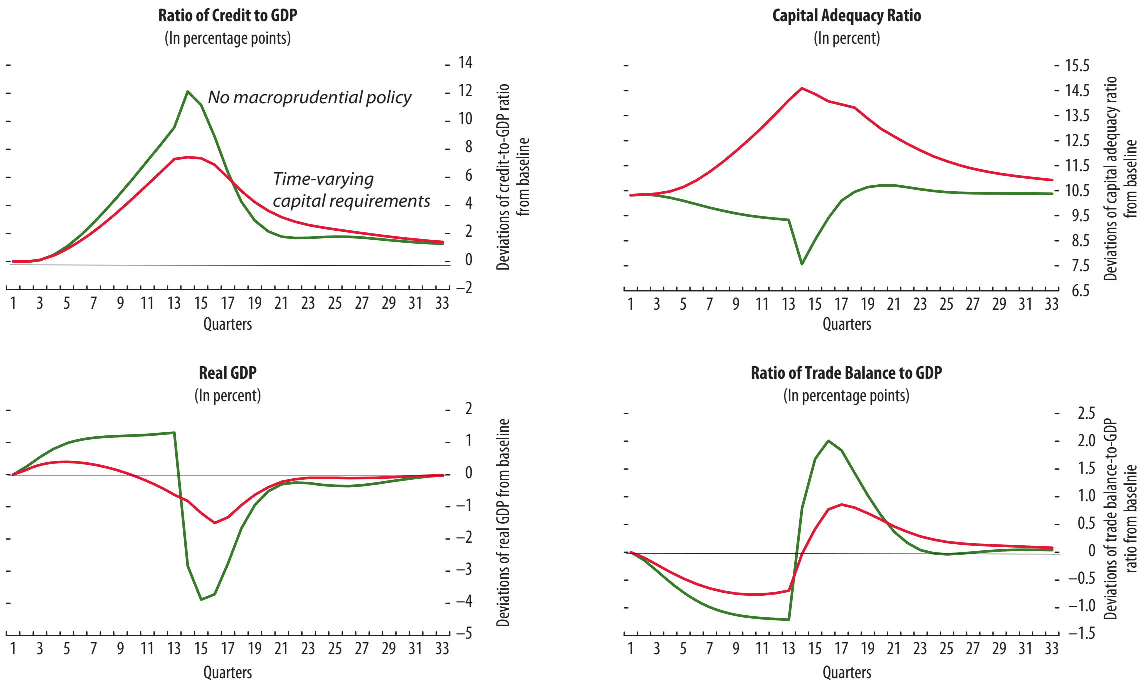
In the case of flexible exchange rates, the model shows that time-varying capital requirements are successful in dampening the credit cycle and in building buffers (Figure 3.6). For comparison, the time path of each variable is computed when capital requirements are fixed as well as when they are time varying. In either case, monetary policy operates in a flexible exchange rate regime. The fixed capital requirements and monetary policy are not enough to dampen the boom-bust asset-price cycle, mainly because these policies are not sufficient to prevent the procyclicality of capital and credit. The introduction of the countercyclical capital buffers dampens both the real and financial cycles and reduces the adverse impact of the crisis on the level of real GDP. In the model, raising capital is very costly for banks, so they pass on the higher cost of the macroprudential capital requirement by raising lending rates (by a "regulatory" spread). The dampening occurs both through reduced risk taking (the application of the regulatory lending spread) and the creation of a buffer for the crisis.[38] Furthermore, the long-run volatilities of consumption, output, inflation, and credit are reduced due to dynamic capital requirements (denoted by a proactive capital requirement and then by a more aggressive capital requirement, as illustrated in Table 3.3).

The model could also be used to illustrate the economic cost of not understanding the source of real and financial cycles. In general, the cost of misidentifying the shocks could be very high. For instance, the economy may be going through a healthy productivity rise; if policymakers mistake it for an asset-price boom and impose time-varying capital requirements, they could significantly dampen the level of output for a prolonged period (Figure 3.7). Hence, it would be useful to look at developments in productivity growth, in the tradables sector for instance, to judge whether the observed cycles in the real and financial sectors could be a macroprudential concern. This is an instance in which macroprudential

[37]See IMF (2011b). Monetary policy, with a separate objective and policy tool, is characterized by a simple inflation-targeting rule in a flexible exchange rate regime. Banks are subject to fixed microprudential capital requirements to address idiosyncratic credit risk. The macroprudential policy requirements are added due to concerns about banks' exposure to aggregate risk. Even though the risk could be addressed by containing the cycles of financial risk and addressing the interconnectedness of financial institutions, only the former is taken up in this section, as interconnectedness has not yet been introduced in the structural model.

[38]Banks do not expand credit as much during the boom phase because they fear they might not be able to satisfy the higher requirements when they are confronted with a future reversal. Hence, leverage is endogenously less procyclical in the model.

Figure 3.6. Effects of Macroprudential Policy: Time-Varying Capital Requirements for an Asset-Price Shock



Source: IMF staff estimates.

Note: Time-varying capital requirements are designed as a rule that depends upon the growth in the credit-to-GDP ratio. "No macroprudential policy" includes fixed microprudential capital requirements. The baseline assumes no shock and no macroprudential policy.

Table 3.3. Long-Run Steady-State Volatilities, by Type of Capital Requirement

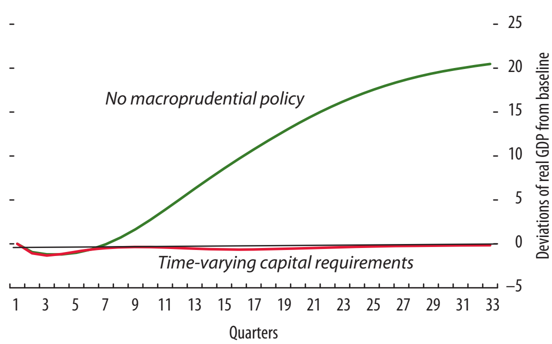
	Fixed (Microprudential)	Countercyclical (Mild)	Countercyclical (Aggressive)
Consumption	1.00	0.80	0.59
GDP	0.56	0.44	0.32
Inflation	0.25	0.20	0.16
Real credit	1.74	1.44	1.13

Source: IMF staff estimates.

Note: The long-run (asymptotic, steady-state) volatility implied by the occurrence of the asset price bubble shock is calculated above. The size of the shock is normalized so that the implied contribution to the standard deviations in real consumption is 1 percent. The table then shows the reductions in the implied standard deviations for four variables with different types of capital requirement policies.

Figure 3.7. Effects of Productivity Shock and Time-Varying Capital Requirements on Real GDP

(In percent)



Source: IMF staff estimates.

Note: See note to Figure 3.6.

and monetary policymakers could coordinate to form an informed view of the source of shocks.[39]

A parallel analysis of a fixed exchange rate economy shows that the qualitative impact of the macroprudential tool is virtually identical to that in the case of a flexible exchange rate economy. Hence, properly designed time-varying capital requirements for banks can help mitigate financial cycles for economies with different exchange rate regimes. Indeed, actual country practices show that the effectiveness of macroprudential tools in reducing procyclicality is not influenced by differences in economic structures—degree of economic development, the exchange rate regime, or the size of the financial sector (Box 3.4).

However, one of the lessons from the analysis based on the structural model was that the combination of fixed exchange rates and widespread foreign currency lending could amplify the boom-bust cycles created by the shocks. Fixed exchange rates tend to reduce the perception of exchange rate risks in the buildup stage, which encourages both banks and households (without a natural hedge against exchange rate risks) to accumulate loans in foreign currency. Overall credit growth increases rapidly until the possibility of a change in exchange rate regime amplifies the effect of any crisis. This observation could be a reason for more aggressive capital requirements (see Table 3.3) or a macroprudential rule based on growth in foreign currency lending, for instance, and provides an added reason in such economies for close coordination between macroprudential and exchange rate policies.

Key results:

- Combining empirical analysis with insights from a structural model can aid macroprudential policymakers in calibrating their macroprudential tools properly.
- Countercyclical capital buffers work to reduce risks of financial and economic disruptions.
- Knowledge of the type of shock is relevant to avoid the costly imposition of macroprudential tools when they are not warranted.
- The countercyclical capital buffer works across different exchange rate regimes.

[39]It can be argued that although the two policies, monetary and macroprudential, have different objectives and use different tools, their eventual impact on credit aggregates and on real economic cycles can be very similar, potentially reinforcing or offsetting each other. See Kannan, Rabanal, and Scott (2009a) on how welfare improves when a credit aggregate is included in the monetary policy rule; and Jácome and others (forthcoming) on institutional arrangements for macroprudential policies.

Conclusions and Practical Guidelines

Operationalizing macroprudential policies is a multifaceted task, and the analysis here takes concrete steps along several paths to reach this goal. It uses a macroeconomic structural model with an explicitly embedded financial sector to explore how different indicators behave in response to various sources of shocks. Empirical exercises provide additional information on which variables are best for flagging the buildup of risk. Further, the analysis suggests a set of high-frequency indicators that could alert policymakers to imminent arrival of financial distress. The structural model also offers insights into how one popular macroprudential tool—countercyclical capital requirements—would work under different types of shocks and accounting for the financial linkages to the real side of the economy. The results yield the following set of practical guidelines.

Sources of shocks. Effective monitoring of systemic risk and effective policy responses depend critically on accurate identification of the sources of shocks. The chapter finds that the source of shocks drives movements in variables that are associated with systemic risk buildup. Differences in the financial structure of the economy change the magnitude of the effects of shocks but not their direction.

Credit and other aggregates. Among slow-moving indicators of the buildup of risk, credit aggregates are useful but need to be complemented by other indicators. Countries with a low level of credit might experience rapid credit growth and authorities may view it as a natural part of the development process, but credit growth that greatly exceeds economic growth would still be a signal of risk buildup particularly if some of the other indicators are signaling it as well.

Box 3.4. An Empirical Analysis of the Effectiveness of Macroprudential Instruments

A number of countries employ macroprudential instruments to contain systemic risk. The effectiveness of 10 such instruments is examined here.

Through a panel regression analysis, we examine the effectiveness of 10 instruments on four types of risks considered systemic by country authorities.[1] These risks are associated with excessive: (i) credit growth, (ii) systemic liquidity, (iii) leverage, and (iv) size and volatility of capital flows.[2] The regression analysis examines whether the instruments limit the procyclicality of each of the risks—that is, the tendency of the risks to amplify the business cycle. The data for the regressions cover 49 countries, quarterly from 2000 to 2010, and were collected in the 2010 IMF survey on financial stability and macroprudential policy (IMF, 2011b).

Here are three key challenges in the data and the methods used to address them in the regressions:

- *Disentangling the effect of macroprudential instruments from those of other policies, especially monetary and fiscal policies.* Interest rates and real activity indicators (GDP growth) were used to control for the effects of macroeconomic policies.
- *Inferring the general effect of macroprudential instruments in the context of country-specific characteristics.* Dummy variables were used to control for the type of exchange rate regime, the size of the financial sector, and the degree of economic development. The fixed effect in the panel regression takes into account other unobserved country-specific characteristics.
- *Avoiding estimation biases to ensure a correct quantification of the effect of macroprudential instruments.* The regression employed system GMM (generalized method of moments), widely used for panel data with endogenous explanatory variables.

The regression results suggest that some macroprudential instruments reduce procyclicality, defined here as the correlation of systemic risk—credit growth, liquidity, leverage, and capital flows—with GDP growth. In particular, for credit and leverage growth, the results in the table show the following:

- Credit-related measures are generally effective in reducing procyclicality. Caps on the LTV ratio reduce the procyclicality of credit growth by 80 percent.[3] This is in line with findings of previous studies that associate higher LTV ratios with higher house price and credit growth over time.[4] Caps on the ratio of debt service to income (DTI) and limits on credit or credit growth have a similar effect. Caps on the DTI and credit growth also reduce the procyclicality of leverage.
- Liquidity-related measures also reduce procyclicality. Reserve requirements reduce the procyclicality of credit growth by close to 90 percent. The procyclicality of leverage is also reduced.
- Dynamic provisioning reduces the procyclicality of leverage and credit, but the effect of capital-related measures, i.e., countercyclical capital requirements and restrictions on profit distribution, is not obvious. The latter result may reflect the relatively limited use of those measures, and hence the limited number of observations for them, over the period.
- The estimated coefficients of the dummy variables representing the degree of economic development, the type of exchange regimes, and the size of the financial sector are all statistically insignificant.

Note: Prepared by Francesco Columba, Alejo Costa, and Cheng Hoon Lim, drawing on Lim and others (forthcoming).

[1]The 10 instruments are (i) maximum permissible loan-to-value ratio (LTV), (ii) a maximum permissible ratio of debt service to income (DTI), (iii) caps on foreign currency lending, (iv) ceilings on credit or credit growth, (v) limits on net open currency positions or on currency mismatch, (vi) limits on maturity mismatch, (vii) reserve requirements, (viii) countercyclical capital requirements, (ix) dynamic provisioning, and (x) restrictions on profit distribution.

[2]Credit is defined as the change in the inflation-adjusted claims on the private sector by banking and other financial institutions; liquidity is the ratio of liquid assets to short-term liabilities; leverage is assets as a fraction of equity for banking and other financial institutions; and size and volatility of capital flows are measured as the growth rates and volatility of the "other" category in the balance of payments statistics, which mainly captures bank flows.

[3]The coefficient of GDP growth is 0.079, and the coefficient of the cap on the LTV ratio is –0.063 (first column, upper half of table). For every 1 percent increase in GDP growth, credit growth increases by 0.08 percent, but it is offset by 0.06 percent when an LTV cap is introduced, leaving a net effect of 0.02 percent.

[4]See, for instance, IMF (2011c).

Box 3.4 *(continued)*

Overall, 5 of the 10 instruments reduce the correlation between credit growth and GDP growth, and 4 instruments reduce the correlation between leverage and GDP growth. The results were not affected by differences in the degree of economic development, the exchange rate regime or the size of the financial sector, suggesting that, while these factors may influence the choice of macroprudential instruments, the instruments can be effectively used by any country.

The results are promising, but longer time series and better data are needed to confirm them and to evaluate an instrument's effectiveness in specific countries. Indeed, reducing procyclicality does not ensure a directly proportional reduction in financial distress. Moreover, since regulatory and cross-border arbitrage can easily dilute the effectiveness of macroprudential policy, these factors should be taken into account in future analyses.

Effectiveness of Macroprudential Instruments in Reducing Procyclicality

Real Credit Gowth					
Independent Variables	Dependent Variable:[1] Quarterly Credit Growth Rate$_t$				
Quarterly credit growth rate$_{t-1}$	0.082	0.091	0.103	0.082	0.086
	(8.19)***	(15.16)***	(30.07)***	(33.60)***	(2.81)***
GDP growth$_t$	0.079	0.089	0.067	0.087	0.073
	(5.89)***	(10.44)***	(9.39)***	(6.17)***	(5.47)***
Interest rate$_t$	-0.078	-0.080	n.a.[2]	-0.084	-0.062
	(-11.35)***	(-10.48)***		(-19.74)***	(-10.07)***
Caps on loan-to-value ratio[3] × GDP growth$_t$	-0.063				
	(-3.01)**				
Caps on debt-to-income ratio[3] × GDP growth$_t$		-0.098			
		(-4.96)***			
Limits on credit growth[3] × GDP growth$_t$			-0.123		
			(-4.17)***		
Reserve requirements[3] × GDP growth$_t$				-0.080	
				(-4.27)***	
Dynamic provisioning[3] × GDP growth$_t$					-0.178
					(-2.12)**
Leverage Growth					
Independent Variables	Dependent Variable:[1] Quarterly Leverage Growth Rate$_t$				
Quarterly leverage growth rate$_{t-1}$	0.001	-0.012	-0.010	-0.017	-0.017
	(0.12)	(-2.88)***	(-1.62)	(-5.35)***	(-0.73)
GDP growth$_t$	0.035	0.042	0.039	0.088	0.032
	(2.58)**	(5.43)***	(7.15)***	(4.81)***	(4.36)***
Interest rate$_t$	0.059	0.112	0.143	0.136	0.096
	(0.94)	(3.22)***	(5.43)	(4.31)***	(3.09)**
Caps on loan-to-value ratio[3] × GDP growth$_t$	-0.012				
	(-0.44)				
Caps on debt-to-income ratio[3] × GDP growth$_t$		-0.041			
		(-3.35)***			
Limits on credit growth[3] × GDP growth$_t$			-0.032		
			(-1.82)*		
Reserve requirements[3] × GDP growth$_t$				-0.096	
				(-3.44)***	
Dynamic provisioning[3] × GDP growth$_t$					-0.274
					(-4.78)***

Sources: IMF, International Financial Statistics database; and staff estimates.

Note: ***, **, * indicate statistical significance at 1 percent, 5 percent, and 10 percent (two-tail) test levels, respectively.

[1]The dependent variable is (the log change in) real credit growth (top panel) or leverage growth (bottom panel). The interest rate is the nominal long-term interest rate on prime lending, from the IMF's *International Financial Statistics*. The regression includes dummy variables to control for different degrees of flexibility in the exchange rate regime, individual (country) effects, a time trend (year effect), and a dummy variable for the use of other macroprudential policy instruments. Instrumental variables for the policy instrument and the GMM Arellano-Bond estimator are used to address selection bias and endogeneity.

[2]Nonsignificant results when interest rate included.

[3]The coefficient corresponds to the interaction term between GDP growth and a dummy for the respective macroprudential instrument.

- The structural model suggests that even though credit increases in all three constructed scenarios—anticipation of productivity growth, lax lending standards, and asset-price bubbles—the amount of the increase and the persistence of the increase in credit and the decline in capital adequacy ratio are significantly higher in the case of asset price bubbles and lax lending standards.
- The empirical analyses suggest that credit growth, when accompanied by asset price growth, form powerful signals of a developing crisis within the following two years and are good leading indicators. Conditional on credit growing by more than 5 percentage points of GDP, an increase in equity prices of 15 percent or more is sufficient to push crisis probability to 20 percent within two years.
- Among credit aggregates, credit-to-GDP growth and the credit-to-GDP gap perform equally well in panel regressions to signal a risk buildup. The gap is better at predicting crises within one year, while the growth is better at a two-year horizon.

Thresholds. When considering thresholds for various credit aggregates and the timing of preventive policy actions, policymakers need to bear in mind the characteristics of their specific country. For instance:

- In the case of most countries, annual growth of credit-to-GDP is relatively easy to measure and track. For instance, a threshold of 5 percentage points for credit-to-GDP growth works reasonably well in signaling a crisis: it reduces the chances of missing a crisis while lowering the chances of issuing a false signal. For countries with low levels of the credit-to-GDP ratio, a slightly higher threshold might be applicable, although attention to country-specific circumstances would be important to consider.
- Setting a threshold of 5 percentage points of GDP on a broader measure of credit growth—that includes both bank and cross-border loans to the nonbank private sector—could signal a risk buildup even better. However, analysis of this indicator across countries is hampered by severe data constraints. This weakness points to the importance of collecting consistent cross-border credit information.
- Applying thresholds to the measure of credit-to-GDP gap is complicated and those countries and thresholds for which this measure was analyzed miss most crises.
- Interactions with other variables also matter. The probability of a crisis increases when other indicators—such as asset price growth, foreign liabilities of the economy, and real effective exchange rate—increase as well (as reported in the discussions of the structural model and empirical analyses). In the context of emerging economies, real exchange rate appreciation appears to be a particularly relevant factor.

Near-coincident indicators. Policymakers should also examine high-frequency indicators to prepare for the potential near-term materialization of a crisis and the possible release of built-up buffers.

- Among such indicators, this chapter finds that a time-varying version of the CoVaR using U.S. institutions performed best in predicting materialization of financial system stress in the United States during the last crisis. Since this indicator was constructed using the LIBOR-OIS spread and the yield curve, a combination of these two variables may be a good indicator of potential materialization of stress for countries for which they are available.
- Policymakers may have to rely on actual information on cross-institutional exposures to assess the potential for domino effects if a crisis were to materialize. The chapter is unable to find any market-based, high-frequency indicators that adequately signal a buildup of interconnectedness of the system. Enhancing transparency and disclosure requirements (for instance, by requiring OTC derivative trades to clear through central counterparties) could enhance market discipline and lower uncertainty about counterparty risks during a crisis, naturally mitigating domino effects.[40]

Universal use. Some elements of the structure of the real economy are less important than the source of shocks for choosing variables that signal crises and for determining the effectiveness of macroprudential policies. Thus, policymakers should devote resources and coordinate with each other to better understand the sources of shocks. The set of macroprudential tools can be relatively homogeneous across different economies, which should help to facilitate policy

[40]See IMF (2010c).

coordination at the international level. However, the *calibration* of policy instruments—especially those based on thresholds for different indicators—differ according to country-specific circumstances.

Managed exchange rate regimes. Even though the signaling variables and tools may be similar across most economies, certain exchange rate regimes together with some financial sector characteristics are shown to amplify the transmission mechanisms of all shocks. Managed exchange rates and the use of loans denominated in foreign currency are such specific characteristics. Thus, close coordination of exchange rate, monetary, and macroprudential policies is essential to achieve a more stable financial sector and real economy.

In conclusion, operationalizing macroprudential policies means progressing on a number of fronts: monitoring risk buildup, detecting when risks have materialized, and applying macroprudential policy tools to minimize the risks. The insights from the modeling and empirical work here advance our understanding of each of the interrelated tasks in the still-nascent area of macroprudential policymaking.

Annex 3.1. Description of the Structural Model[1]

The dynamic stochastic general equilibrium (DSGE) model used for the policy simulation experiments in the chapter is further described here. The behavior of individual agents in the model is derived from explicit optimizing problems, while the aggregate outcomes arise as a result of general equilibrium conditions assumed to prevail at all times.

The novel feature of the model is a fully endogenous feedback loop between a real economy and a financial (or more specifically, commercial banking) sector. The framework is designed to address the time dimension of systemic risk that is related to the exposure of all banks to the aggregate (credit) risk from procyclicality.

The feedback loop builds upon the following elements: (i) banks act as agents with their own net worth; (ii) bank loans are introduced whereby the loan value (credit risk) contains both idiosyncratic (diversifiable) and aggregate (nondiversifiable) components of risk, and loans cannot be renegotiated by the borrower after the shocks have occurred; (iii) aggregate risk associated with bank loans is derived from the value of underlying collateral assets; (iv) prudential capital regulation, at both the micro and macro levels, is introduced as an incentive-based mechanism; and (v) market rigidities that apply to equity (or bank capital) make *instantaneous* market recapitalization prohibitively expensive.

Real Sector

The real sector mimics a standard small open-economy DSGE model with sufficient short- and medium-term imperfections (rigidities, adjustment costs, etc.) to generate realistic business-cycle dynamics. Some of the most important characteristics of the real sector are listed below:

- One *production* function, but two separate markets: goods distributed locally and goods sold internationally. Local households and nonfinancial firms purchase locally produced final goods and directly imported final goods. Local goods are produced using three input factors: labor, capital, and intermediate imports.
- *Exports* are assembled by combining local value added with re-exports in fixed proportion. Export assembly has its own productivity process in addition to the overall total factor productivity introduced in the domestic production function. Adjustments to export production (in response, for instance, to terms-of-trade shocks) are costly and hence distributed over time. The terms of trade (the price of exports divided by the price of imports) are exogenous.
- The model structure is capable of encompassing a relatively large range of *different types of open economies*. For instance, the expenditure switching effects and the sensitivity of the real sector, including imports and exports, to exchange rate movements can be modified by changes in a number of structural parameters.
- *Households* play two roles. They act as consumers and investors and supply labor. Each investor makes two joint decisions: purchasing productive capital and acquiring bank loans. The investor uses his or her capital to collateralize the loan; the return on capital has an idiosyncratic component making the investors heterogeneous ex ante. The fact that the model considers only physical capital and no other types of assets (such as housing, stocks, etc.) is immaterial for the results: the main conclusions and policy implications would remain unaffected.

Banks

Banks make two types of decisions: asset related—providing loans to nonfinancial individuals—and liability related—choosing the optimal proportion of bank capital. To keep the problem tractable, the two decisions are made by two separate “branches” of the bank: a retail lending branch and a wholesale finance branch. Each branch takes the other’s behavior as given; in other words, they do not internalize the other’s reaction function.

Asset Decisions

Bank loans are noncontingent in that the lending rate is agreed upon at the beginning and cannot be subsequently adjusted in response to ex post shocks;

[1]Prepared by Jaromír Beneš.

noncontingent contracts are used, for instance, by Cúrdia (2007). Bank lending is subject to a financial friction (limited enforcement), which gives the borrower an incentive to default and let the lender seize the collateral.[2] The implications of this limited enforcement setup are very similar to those in the "costly state verification model" of Bernanke, Gertler, and Gilchrist (1999). Here, however, the assumptions are kept deliberately simpler to make the model and its parameterization more tractable in practical application.

As a result of the financial frictions, bank lending is risky, and the credit risk has both idiosyncratic (diversifiable) and aggregate (nondiversifiable) components. Each risk-neutral retail branch specifies a lending supply curve by equating the expected return on a loan with the marginal cost (or opportunity cost) of lending determined by the wholesale branch. The lending supply curve is characterized so that the amount loaned is positively related to the price of capital available to collateralize the loan.

Formally, the optimal contract between the bank and each individual household member maximizes the expected utility of the household as a whole subject to a participation constraint of the bank. Expressing only the relevant terms, an individual loan, L^i, the corresponding lending rate R^i_L, and the amount of productive capital, K^i, are chosen to maximize:[3]

$$E_t\Big\{L^i_t - P_{K,t}K^i_t + \frac{\beta\Lambda_{t+1}}{\Lambda_t}\left[-R^i_{L,t}L^i_t + R^i_{K,t+1}P_{K,t}K^i_t\right] + \Phi^i_t\left[R^i_{L,t}L^i_t\left(1 - vF_i(\overline{R}^i_{K,t})\right) - \overline{R}_{A,t}L^i_t\right]\Big\}$$

where v is the loss given default, and F_i is the cumulative distribution function for the individual return on capital (see below). The price of capital, P_K, the shadow value of wealth of the household as a whole, Λ, and the opportunity cost, $\overline{R}_A$, are taken as given. Furthermore, the cutoff return on capital, $\overline{R}^i_K$, is given by

$$\overline{R}^i_{K,t} = \frac{R^i_{L,t}L^i_t}{P_{K,t}K^i_t} = R^i_{L,t}l^i_t$$

where l^i_t denotes the loan-to-value (LTV) ratio.

The retail branch extends loans to a large number of individuals to diversify away the idiosyncratic component of credit risk. The bank still remains exposed to the aggregate component of the risk. This makes the distribution of the return on an individual loan different from the distribution of the return on a whole portfolio of loans, and the actual ex post return on loans possibly different from its ex ante expectations. The distribution of the return on bank assets derives, in general, from the characteristics of the aggregate return on productive capital used as collateral.

Formally, the distribution of the individual return on capital is modeled as a multiplicative mean-preserving spread over the aggregate return on capital.

$$\begin{aligned} R^i_{K,t+1} &= R_{K,t+1}\rho_{t+1} \\ R^i_{K,t+1} &\sim F_i \\ R_{K,t+1} &\sim F_R \\ \rho_{t+1} &\sim F_\rho \end{aligned}$$

where R^i_K is the individual return on capital with distribution F_i; R_K is the aggregate component of the return on capital with distribution F_R; and ρ is the idiosyncratic component with distribution F_ρ.

The idiosyncratic component is independent of the aggregate component and is centered around 1. The aggregate component is implied endogenously by the model. When choosing its debt liabilities (deposits and foreign borrowing) and equity liabilities (bank capital), the wholesale branch is constrained by capital regulation. As in Milne (2002), the capital regulation applies to the ex post values of bank assets and liabilities and specifies a penalty for banks whose capital adequacy ratio falls below a prescribed minimum:

$$\begin{aligned} NW_t < \tau_t AA_t &\Rightarrow -vL_{t-1} \\ AA_t &= R_{A,t}L_{t-1} \\ NW_t &= R_{A,t}L_{t-1} - R_{F,t-1}F_{t-1} \end{aligned}$$

where NW is the ex post net worth of the bank, AA is the ex post value of its assets, R_A is the actual

[2]In that case, the bank can pay a collection cost to make the defaulted borrower repay the loan in full; the probability that the bank succeeds is set to a number arbitrarily close to 1.

[3]The terms related to a situation in which the household member succeeds in walking away from the loan are dropped; the probability of such an outcome is set to a numerically negligible value.

return on bank assets, τ is the (possibly time-varying) regulatory capital minimum, and υ is the penalty as a percentage of the bank's assets.

Liability Decisions

Acquisition of bank capital is subject to two constraints. First, it is prohibitively costly for banks to issue new equity within the regulatory evaluation period after the true gains or losses are realized. Second, there are convex costs of acquiring new capital between every two periods, as in Estrella (2004)—the cost of capital becomes more than proportionately expensive in the second period. The high cost of capital makes retained earnings an important source of net worth. The costs are symmetric in that they also affect banks' dividend policies.

Putting the two above assumptions together, one can formally write the bank's optimal liability choice as follows. Choose the amount of loans, L, the amount of bank capital (or equity), E, and the amount of bank's funding liability (deposits, foreign funds), D, to maximize the expected payoff to the shareholders subject to the balance sheet identity that loans need to be equal to capital plus funding:

$$\max \left\{ \mathrm{E}_t \{ R_{A,t+1} L_t - R_{F,t} D_t - \upsilon L_t F_A(\bar{R}_{A,t}) - \frac{\xi}{2} \mathrm{E}_t(\log E_t - \log \bar{E}_t)^2 \} \right\}$$

subject to

$$L_t = E_t + D_t$$

where R_A is the return on bank assets and F_A is the distribution of this return on assets. The cutoff return on the bank's assets (that is, the portfolio of diversified loans), $\bar{R}_A$, is given by

$$\bar{R}_{A,t} = R_{F,t} \frac{1 - e_t}{1 - \tau_t}$$

where e_t represents the capital-to-loan ratio at time t

$$e_t = \frac{E_t}{L_t}$$

and the reference level of bank capital, $\bar{E}$, is set to retained earnings from the previous period, that is, the previous level of bank capital times the current gross return on equity:

$$\bar{E}_t = R_{E,t} E_{t-1}$$

In the simulations, the equity issuance parameter is set to infinity so that new capital can be acquired only through retained earnings.

Furthermore, the distribution of the portfolio of loans can be derived endogenously from the distribution of the aggregate return on capital (that is, on the collateralizing asset). For each cutoff return on assets there is a unique corresponding aggregate return on capital; the two are linked through the following relationship:

$$\bar{R}_A = R_{L,t} \left[1 - \upsilon F_i \left(\frac{R_{L,t}}{\bar{R}_{K,t}} l_t \right) \right]$$

Since each bank's return on its loan portfolio is uncertain, the optimal choice of capital gives rise to an endogenous and time-varying capital buffer in excess of the regulatory minimum. Also, the wholesale branch specifies a marginal cost of lending taken as given by the retail branch. The marginal cost is, in general, driven by the cost of bank liabilities, by the distance to regulatory minimum, and by the characteristics of the distribution of uncertainty associated with the bank's assets.

Monetary and Prudential Policies

In the simulations, monetary policy is characterized by a simple inflation-targeting rule and a flexible exchange rate. Some of the experiments also show the outcomes for economies with considerable financial dollarization. In those instances, the nominal exchange rate is included as a tool of defense against adverse balance sheet effects of the private sector that could, in turn, increase credit risk in banks.[4]

Bank capital is subject to fixed microprudential capital requirements. Furthermore, macroprudential capital requirements are also used in some of the experiments. The macroprudential requirements are

[4]Such a policy is not termed a managed exchange rate regime because it is typically implemented through sterilized interventions.

added as a surcharge on top of the microprudential ones and follow a time-varying rule based on changes in the credit-to-GDP ratio.

Parameterizing the Model

In the baseline calibration of the model, we considered several aspects and stylized facts of a number of small, open, emerging market economies in Europe, Latin America, and Asia. We arrived at four basic groups of parameters: steady-state, transitory, policy, and financial. The steady-state parameters were calibrated with various long-run structural indicators such as average export and import shares of GDP, the net investment position, the net foreign asset position of the banking sector alone, employment in the exporting industries, composition of tradables and nontradables in final prices, and so on. The transitory parameters were set to produce plausible dynamic responses, especially to match existing empirical evidence on the exchange rate pass-through into final prices and the cyclicality of demand components. The policy parameters were chosen to guarantee realistic policy trade-offs (measured by indicators such as sacrifice ratio or the costs of temporarily inactive policy).

The calibration of the financial sector, in particular the various aspects of the distribution of risks, was largely based on a heuristic method: finding sensible thresholds at which the built-in nonlinearities become influential in the interactions between real economic activity and the bank balance sheets. However, the techniques of empirical validation for such financial characteristics in models with macroeconomic-financial linkages are in their infancy. Therefore, the model simulations presented in the main text should be considered more as thinking devices rather than empirically accurate predictions.

Annex. 3.2. Predicting the Probability of a Banking Crisis[1]

The probability of a banking crisis, presented in the main text, was estimated with the following methodology (for details, see Lund-Jensen, forthcoming). In the empirical analysis, the probability of a banking crisis is a function of a vector of systemic risk indicators. The relationship can be approximated by a probit panel data model with country fixed effects:

$$Pr(y_{i,t}=1|\mathbf{x}_{i,t-h}) = \Phi(\alpha_i + \mathbf{x}_{i,t-h}\boldsymbol{\theta}) \qquad (1)$$

where $y_{i,t}$ denotes a binary banking crisis variable; $\mathbf{x}_{i,t-h}$ is a row vector of indicator variables; α_i denotes the fixed effect for country i; Φ is the cumulative distribution function of a standard normal distribution; and $\boldsymbol{\theta}$ is a column vector of unknown parameters to be estimated. Note that all the indicator variables are known at time $t-h$. This analysis considers forecast horizons at one, two, and three years.

We adopt the Laeven and Valencia (2010) definition under which a banking crisis is systemic if two conditions are present: (i) significant signs of financial distress in the banking system (as indicated by significant bank runs, losses in the banking system, and bank liquidations); and (ii) significant banking policy interventions in response to significant losses in the banking system. See Laeven and Valencia (2010) for more details.

The use of the probit framework implies that the marginal effect—the effect on the crisis probability due to an incremental increase in an indicator variable—is nonlinear and depends on the value of the fixed structure of the economy, α_i, and the level of the indicator variables. For example, the marginal effect of an incremental increase in $x_{ij,t-h}$ (an element of $\mathbf{x}_{i,t-h}$) can be described as:

$$\partial Pr(y_{i,t}=1|\mathbf{x}_{i,t-h}) / \partial x_{ij,t-h} = \varphi(\alpha_i + \mathbf{x}_{i,t-h}\boldsymbol{\theta})\theta_j \qquad (2)$$

where φ denotes the probability density function of a standard normal distribution. The marginal effect is allowed to vary by country via the fixed effect, the α_i. The fixed effects denote the time-invariant characteristics that affect crisis probability in a country. Countries with fixed effects higher (lower) than the 80th (20th) percentile of all fixed effects are termed *high risk (low risk)*.

The probabilities of a banking crisis based on the yearly change in the credit-to-GDP (CtG) ratio and the gap between the CtG ratio and its trend are estimated on a model specification with a single indicator variable using an unbalanced panel of 94 countries for the period 1975–2010 (Table 3.4). Both credit measures have a significant positive influence on the probability of a systemic banking crisis at a one- to two-year forecast horizon. For a high-risk country, evaluated at the median value of the indicator variable, a 1 percentage point increase in the CtG gap will increase the probability of a systemic banking crisis by 0.34 percentage point in the following year and by 0.24 percentage point the year after. Similarly, a 1 percentage point change in the year-on-year CtG growth will increase the probability of a systemic banking crisis by 0.23 percentage point in the following year and 0.24 percentage point the year after.

The marginal effect of the annual change in the CtG ratio at a two-year forecast horizon for different growth levels has been estimated (Figure 3.8) by implementing equation (2) using the estimate from Table 3.4 and θ = 1.69. The marginal effects (ME) are calculated as follows:

$$ME_{high\ risk} = \varphi(\alpha_{high\ risk} + \Delta CtG_{t-2}*1.69)*1.69 \qquad (3a)$$

$$ME_{low\ risk} = \varphi(\alpha_{low\ risk} + \Delta CtG_{t-2}*1.69)*1.69 \qquad (3b)$$

where $\alpha_{high\ risk} = -1.44$ and $\alpha_{low\ risk} = -1.91$ are the 80th and 20th percentile country fixed effects, respectively. It is clear that the model structure implies that there is a positive relationship between the marginal effect and the level of CtG growth. For example, when the change in the CtG ratio is at its 95th percentile level, the marginal effect is 0.30 percentage point for a high-risk country rather than 0.24 percentage point at the 50th percentile.

Estimated model specifications were obtained for interactions of credit aggregates with other indicator variables, including for the change in the CtG ratio with the change in equity prices (Table 3.5).[2] That estimation is based on an unbalanced panel of 36

[1]Prepared by Kasper Lund-Jensen.

[2]This model specification corresponds to $\mathbf{x}_{i,t-h} = (\Delta CtG_{i,t-h}, \Delta\ln(\text{equity price})_{i,t-h})$ and $\boldsymbol{\theta} = (\theta_1, \theta_2)^T$ in equation (1).

Table 3.4. Determinants of Systemic Banking Crises: Single-Indicator Probit Model

Change in Credit-to-GDP Ratio
(In percentage points)

Lag length (in years)	Coefficient Estimate (θ)	*t*-Statistic	Marginal Effect (high risk)*	Marginal Effect (low risk)**	Median Credit-to-GDP Growth
1	1.42	2.29	0.23	0.09	0.62
2	1.69	2.14	0.24	0.11	0.61
3	1.04	1.37	0.18	0.07	0.56

Credit-to-GDP Gap
(In percentage points)

Lag length (in years)	Coefficient Estimate (θ)	*t*-Statistic	Marginal Effect (high risk)*	Marginal Effect (low risk)**	Median Credit-to-GDP Gap
1	2.01	2.36	0.34	0.13	0.33
2	1.27	1.48	0.24	0.08	0.24
3	0.09	0.11	0.02	0.01	0.16

Source: IMF staff estimates.

Note: The dependent variable is a binary systemic banking crises variable from Laeven and Valencia (2010). The data are from an unbalanced annual panel for the period 1975–2010. The model parameters are estimated using country fixed effects for 94 countries. Models with different lags are estimated using the same data sample. The marginal effects (ME) are evaluated at the median value of the explanatory variable in the last column. The change in the credit-to-GDP ratio is calculated as follows: $\Delta CtG_t = CtG_t - CtG_{t\text{-}1}$.The credit-to-GDP gap is estimated using a single-sided Hodrick-Prescott filter with a smoothing parameter of 100 and five initial observations. Model specification: Prob(Banking Crisis$_{i,t=1}$|$x_{i,t\text{-}h}$) = $\theta(\alpha_i + \theta^* x_{i,t\text{-}h})$.

* A high-risk country is defined as the 80th percentile country fixed effect.

** A low-risk country is defined as the 20th percentile country fixed effect.

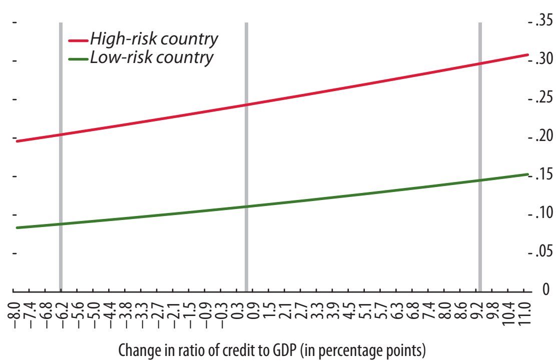
countries for the period 1975–2010. The change in the CtG ratio was found to have a significant positive impact on the crisis probability at all three forecast horizons. At a two-year horizon, the growth in equity prices also has a significant positive impact on the crisis probability. Based on this model specification, the crisis probability at a two-year horizon can be estimated as:

$$\Phi(\alpha_{high\ risk} + \Delta CtG_{t-2}{*}3.64 + \Delta \ln(\text{equity price})_{t-2}{*}0.67) \qquad (4)$$

where $\alpha_{high\ risk} = -1.26$ denotes the 80th percentile country fixed effect. The predicted crisis probabilities for different values of change in equity prices and the CtG ratio are illustrated in Figure 3.4 in the main text.

The United States experienced two systemic banking crises during the 1975–2009 period according to Laeven and Valencia (2010): one beginning in 1988 and the other in 2007. Figure 3.5 in the main text depicts the out-of-sample

Figure 3.8. Marginal Effect on Probability of Crisis of Change in Ratio of Credit to GDP
(In percentage points)



Source: IMF staff estimates.

Note: Effect with a two-year lag. The parameters are estimated using a fixed-effect probit panel model with a single predictor (see Table 3.4 for details). The estimation is based on an unbalanced annual panel of 94 countries for the period 1975–2010. A high-risk country is defined as the 80th percentile country fixed effect; a low-risk country is defined as the 20th percentile country fixed effect. The vertical lines illustrate the 5th, 50th, and 95th percentiles of growth in the credit-to-GDP ratio in the sample.

forecast of the U.S. crisis probability for the period 2001–09. The forecasts were constructed by estimating a single indicator probit model with country fixed effects for 1975–2000 based on the CtG gap and the change in the CtG ratio.[3] The results were similar to the estimation based on the entire sample, 1975–2010, in Table 3.4. Both indicators were again found to have a positive significant impact on the crisis probability at a one-year forecast horizon. The out-of-sample forecasts were simply constructed as follows:

$$Pr(y_{US,t}=1|\mathbf{x}_{i,t-1}) = \Phi(\alpha_{US} + x_{US,t}{*}\theta_{2000}), \quad (5)$$
$$t = 2001, \ldots, 2009$$

where θ_{2000} denotes the parameter estimate based on the 1975–2000 sample.

[3]The change in the CtG ratio has a significant impact on the crisis probability at both a one- and two-year forecast horizon (Table 3.5). To incorporate information from both lags, the change in the CtG ratio was defined in the forecasting exercise as $\Delta CtG_t = (CtG_t - CtG_{t-2})/2$.

Table 3.5. Determinants of Systemic Banking Crises: Two-Indicator Probit Model

Change in Credit-to-GDP Ratio
(In percentage points)

Lag (length in years)	Coefficient Estimate (θ_1)	*t*-Statistic	Marginal Effect (high risk)*	Marginal Effect (low risk)**	Median Credit-to-GDP Growth
1	5.28	2.61	1.06	0.35	1.9
2	3.64	1.92	0.78	0.31	1.8
3	4.67	2.32	1.00	0.32	1.7

Equity Growth
(In percent)

Lag (length in years)	Coefficient Estimate (θ_2)	*t*-Statistic	Marginal Effect (high risk)*	Marginal Effect (low risk)**	Median Equity Price Growth
1	-0.01	-0.03	0.00	-0.00	12.8
2	0.67	2.35	0.14	0.06	10.6
3	-0.23	-0.80	-0.05	-0.02	12.8

Source: IMF staff estimates.

Note: The dependent variable is a binary systemic banking crises variable from Laeven and Valencia (2010). The data are from an unbalanced annual panel for the period 1975–2010. The model parameters are estimated using country fixed effects for 36 countries. Models with different lags are estimated using the same data sample. The marginal effects (ME) are evaluated at the median value of the explanatory variables in the last column. The change in the credit-to-GDP ratio is calculated as: $\Delta CtG_t = CtG_t - CtG_{t-1}$. Equity price growth is calculated as: $\Delta\ln(\text{Equity Price})_t = \ln(\text{Equity Price}_t) - \ln(\text{Equity Price}_{t-1})$.

Model specification: $\text{Prob(Banking Crisis}_{i,t=1}|x_{i,t-h}) = \Phi(\alpha_i + \theta_1{*}\,\Delta CtG_{t-h} + \theta_2{*}\,\Delta\ln(\text{Equity Price})_{t-h})$

* A high-risk country is defined as the 80th percentile country fixed effect.

* *A low-risk country is defined as the 20th percentile country fixed effect.

Annex. 3.3. Finding a Robust Set of Near-Coincident Indicators[1]

The methodologies for comparing high-frequency indicators presented in Box 3.3 are described here (see Arsov and others, forthcoming, for details). For the period from December 30, 2002, to April 11, 2011, daily data on (weekly) equity returns of 17 domestic financial institutions in the United States were used to create the abnormal returns. The data used to construct each of the indicators varied. All estimations were done on the weekly version of the dataset.

The ten indicators used for comparison were:

- **Yield curve:** The difference between the yield on 10-year Treasury bonds and 3-month Treasury bills.
- **Time-varying CoVaR:** Conditional Value at Risk or CoVaR (Adrian and Brunnermeier, 2010) is the Value at Risk of the financial system conditional on institutions being in distress. An institution's contribution to systemic risk is the difference between the CoVaR for tail-risk episodes and the CoVaR at the median state. The time-varying CoVaR is based on the returns of the market value of assets (Moody's KMV) and is estimated by quantile regressions of the returns of the financial system on the returns of an institution and other variables. For the exercise in this section, the yield curve and the LIBOR-OIS spread are used as these other variables.[2]
- **Rolling CoVaR:** CoVaR based on (200-week) rolling quantile regressions of weekly returns on the market value of assets. It does not take account of other variables.
- **Joint probability of distress (JPoD):** The joint probability of distress of all institutions included in a predefined financial system. It is based on a nonlinear, time-varying measure of "tail dependence" constructed with a multivariate distribution of individual institutions' probability distributions of their implied asset value movements (Segoviano and Goodhart, 2009).
- **Credit Suisse Fear Barometer:** An index of investor sentiment that prices zero-premium collars that expire in three months. The collar is implemented by the selling of a three-month, 10 percent out-of-the-money S&P 500 call option and using the proceeds to buy a three-month out-of-the-money S&P 500 put option of equal value.
- **Distance to default (DD) of banks:** The number of standard deviations by which the banking system is away from the default point—the point at which the liabilities of the banks are just equal to the market value of assets (De Nicolò and Kwast, 2002).
- **Diebold-Yilmaz:** A measure of spillovers based on the matrix of variance decompositions derived from 80-week rolling vector autoregressions of financial institutions' weekly credit default swaps spread returns (Diebold and Yilmaz, 2009).
- **VIX:** The Chicago Board Options Exchange Volatility Index calculated from S&P 500 option prices, measuring the market's expectation of future volatility over the next thirty-day period.
- **LIBOR-OIS spread:** A measure of the risk of default associated with lending to other banks in the LIBOR market.
- **Systemic Liquidity Risk Indicator (SLRI):** Measures the breakdown of arbitrage conditions in major markets, and is a global indicator of liquidity stress (Severo, forthcoming; IMF, 2011a).

The results were based on three types of tests on the systemic risk indicators. The dependent variables, that is, the event variables to test against, for the first two tests were Systemic Financial Stress (SFS) and the extreme SFS, respectively. The SFS is the fraction of banks experiencing large negative abnormal returns, with negative abnormal returns persisting for two weeks following the event (further details for the SFS are in Box 3.3). The extreme SFS is an SFS fraction greater than or equal to 0.25.

Forecasting Systemic Stress

The systemic risk indicator should be able to forecast the systemic stress given by the SFS. This attribute is tested using two scores (Table 3.6). The first score is based on a series of Granger Causality

[1]Prepared by Srobona Mitra.

[2]LIBOR is the London Interbank Offered Rate, and OIS is the overnight indexed swap rate.

(GC) tests on weekly data with lag lengths of 52 weeks, 26 weeks, 4 weeks, and 1 week. The score is constructed using *p*-values with significance levels less than 0.01—a larger weight on being significant at 52 weeks than at 1 week. The second score is based on running linear regressions with all four lags in the same regression: 52 weeks, 26 weeks, 4 weeks, and 1 week, and reporting the *p*-values of *t*-tests on each of the four lags in the same regression. The total score is a simple average of the first and the second scores.

Forecasting Systemic Extreme Stress

The systemic risk indicator should be able to forecast extreme events (an SFS greater than or equal to 0.25) with good precision. For this test, logit regressions are estimated with the binary dependent variable equaling 1 if SFS > 0.25 and 0 otherwise. The logistic distribution used in the logit model is skewed and is more appropriate in modeling extreme events, in contrast to the probit, which uses a normal distribution.

The scores are in two groups (Table 3.7): one based on (lower) *p*-values (<0.01) and the other based on McFadden *R*-squares for the logit regressions (the higher the better). The average of the two scores is reported in the last column.

Early Turning Points

Most systemic risk indicators barely showed movements before the crisis. However, nearer to systemic events, these indicators started moving, recording structural breaks in both the level and the persistence of their past relationships. For this exercise, autoregressive regressions with four lags (AR(4)) are estimated for each of the indicators. The Quandt-Andrews breakpoint (QABP) test (unknown breakpoint) is conducted for each of the regressions, testing for breaks both in the mean (the constant term) and persistence process (lagged coefficients in the AR(4) terms). The QABP gives us the possible breakpoint date for each of the indicators for each test (mean and persistence). Table 3.8 shows the dates of these turning points and ranks based on the dates.

Table 3.9 takes the average of the scores from the three tests.

Table 3.6. Granger Causality of Systemic Risk Measure to the Event Indicator

	p-Values for Granger Causality Tests with Various Lags[1]				Scores[2]					*p*-Values for *t*-Test at Each Lag[3]					
Indicators	52 weeks	26 weeks	4 weeks	1 week	52 weeks	26 weeks	4 weeks	1 week	*p*-Value score (1)	52 weeks	26 weeks	4 weeks	1 week	Lag-length score (2)	Average of (1) and (2)
Credit Suisse Fear Barometer	0.1219	0.7200	0.0719	**0.0066**	0	0	0	**1**	0.01	0.24	0.48	0.04	0.95	0.00	0.01
Time-varying CoVaR	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**52**	**26**	**4**	**1**	1.00	0.65	0.63	0.11	0.11	0.00	0.50
Rolling CoVaR	0.0105	0.0212	**0.2429**	**0.0011**	0	0	0	**1**	0.01	0.63	0.57	0.96	0.58	0.00	0.01
DD banks	0.4057	0.0816	0.0662	**0.0000**	0	0	0	**1**	0.01	0.02	0.42	0.26	1.00	0.00	0.01
Systemic liquidity risk index	0.4045	0.0667	0.6771	**0.0015**	0	0	0	**1**	0.01	0.86	0.09	0.17	0.17	0.00	0.01
Diebold-Yilmaz	0.0051	**0.0000**	**0.0000**	**0.0000**	0	0	**4**	**1**	0.06	0.01	0.22	0.64	0.06	0.00	0.03
JPoD	0.0130	**0.0000**	**0.0000**	**0.0000**	0	0	**4**	**1**	0.06	0.15	0.36	0.01	0.07	0.05	0.05
LIBOR-OIS spread	**0.0000**	**0.0000**	**0.0000**	**0.0000**	0	**26**	**4**	**1**	0.37	0.03	0.61	0.00	0.09	0.05	0.21
VIX	**0.0000**	**0.0000**	**0.0000**	**0.0000**	0	**26**	**4**	**1**	0.37	0.26	0.45	0.32	0.01	0.01	0.19
Yield curve	**0.0000**	**0.0000**	0.0967	0.0700	**52**	**26**	0	0	0.94	0.00	0.32	0.24	0.70	0.63	0.78

Source: IMF staff estimates.

Note: Black boldface values are significant at the 1 percent level. Red boldface values are those with no two-way causality (or the causality from the risk indicator to the event indicator is stronger) and are significant at 1 percent level.

[1]Granger Causality (GC) tests with lag-lengths specified in each column. The *p*-values for GC tests under each lag specification are reported here.

[2]Equal to the number of lags if *p*-value is less than 0.01; 0 otherwise.

[3]Based on ordinary-least-squares regression that regresses the Systemic Financial Stress (SFS) indicator on various lags of itself and each of the indicators; the *p*-values are for the *t*-tests for each of the lags in the same regression. The lag-length score is the weighted average of the *p*-values if the *p*-values are less than or equal to 0.01.

$$SFS_t = c + \sum_{s=1,4,26,52} \beta_S SFS_{t-s} + \sum_{s=1,4,26,52} \rho_S \chi_{t-s} + \varepsilon_t$$

Table 3.7. Forecastability of Extreme Events: Logit Regressions

Indicators	*p*-Values for Sum of Lags of Indicators Equal to 0: 6 weeks (weight = 6)	4 weeks (weight = 4)	1 week (weight = 1)	Weighted Average *p*-Values	Score 1	McFadden *R*-Squared: 6 weeks (weight = 6)	4 weeks (weight = 4)	1 week (weight = 1)	McFadden *R*-Squared Scores: Score 2	Average of Score 1 and Score 2
	A	B	C	D	E = 1 – D	F	G	H	I	
Credit Suisse Fear Barometer	0.410	**0.000**	**0.000**	0.22	0.78	0.34	0.29	0.19	0.31	0.54
Time-varying CoVaR	0.594	**0.000**	**0.000**	0.32	0.68	0.41	0.35	0.36	0.38	0.53
Rolling CoVaR	0.651	0.093	**0.002**	0.39	0.61	0.27	0.21	0.13	0.24	0.42
DD banks	**0.008**	0.011	**0.000**	0.01	0.99	0.42	0.38	0.25	0.39	0.69
Systemic liquidity risk index	0.413	0.119	**0.004**	0.27	0.73	0.50	0.34	0.18	0.41	0.57
Diebold-Yilmaz	0.698	**0.001**	**0.000**	0.38	0.62	0.58	0.44	0.32	0.51	0.56
JPoD	0.028	0.030	0.023	0.03	0.97	0.66	0.53	0.21	0.57	0.77
LIBOR-OIS spread	0.921	**0.000**	**0.004**	0.50	0.50	0.40	0.34	0.26	0.37	0.43
VIX	0.069	**0.001**	**0.000**	0.04	0.96	0.34	0.29	0.23	0.31	0.64
Yield curve	0.805	0.528	0.158	0.65	0.35	0.30	0.24	0.12	0.26	0.31

Source: IMF staff estimates.

Note: Black boldface values are significant at the 1 percent level. A binary extreme event variable, *y*, takes the value of 1 if Systemic Financial Stress (SFS) is greater than or equal to 0.25. The two tests are based on three logit regressions with the binary variable as the dependent variable, with lagged dependent variables and lagged indicators, *x*. The lag lengths in each regression are 6, 4, and 1. Column E is based on the weighted average of the *p*-values, and column I is based on the weighted average of the McFadden *R*-squares. The total score is based on a simple average of the two subscores.

Table 3.8. Turning Points: Quandt-Andrews Breakpoint Test on Persistence and Level

	Persistence (ρ_s)		Level (c)		
Indicators	Break Date	Rank Score (higher the better)	Break Date	Rank Score (higher the better)	Average Score
Credit Suisse Fear Barometer	4/30/2007	1.0	4/30/2007	1.0	1.00
Time-varying CoVaR	8/6/2007	0.7	8/6/2007	0.4	0.55
Rolling CoVaR	9/15/2008	0.2	9/15/2008	0.1	0.15
DD banks	7/23/2007	0.8	7/9/2007	0.7	0.75
Systemic liquidity risk index	12/1/2008	0.1	6/16/2008	0.2	0.15
Diebold-Yilmaz	7/3/2007	0.9	7/9/2007	0.7	0.80
JPoD	8/13/2007	0.6	7/2/2007	0.9	0.75
LIBOR-OIS spread	4/7/2008	0.3	8/6/2007	0.4	0.35
VIX	10/29/2007	0.4	5/19/2008	0.3	0.35
Yield curve	8/27/2007	0.5	8/6/2007	0.4	0.45

Source: IMF staff estimates.

Note: Based on autoregressive regressions for each indicator: $\chi_t = c + \sum_{s=1}^{4} \rho_S \chi_{t-s} + \varepsilon_t$.

Table 3.9. Total Score

	Forecasting Stress (Granger Causality, Table 3.6)	Forecasting Extreme Event (logit regressions, Table 3.7)	Turning Point (breakpoint test, Table 3.8)	Average
Time-varying CoVaR	0.50	0.53	0.55	0.53
JPoD	0.05	0.77	0.75	0.53
Credit Suisse Fear Barometer	0.01	0.54	1.00	0.52
Yield curve	0.78	0.31	0.45	0.51
DD Banks	0.01	0.69	0.75	0.48
Diebold-Yilmaz	0.03	0.56	0.80	0.46
VIX	0.19	0.64	0.35	0.39
LIBOR-OIS spread	0.21	0.43	0.35	0.33
Systemic liquidity risk index	0.01	0.57	0.15	0.24
Rolling CoVaR	0.01	0.42	0.15	0.19

Source: IMF staff estimates.

Note: The time-varying CoVaR is derived by using two conditioning state variables: the yield curve and the LIBOR-OIS spread.

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